A DISCRETE-EVENT SIMULATION MODEL OF THE U.S. JUVENILE JUSTICE AND MENTAL HEALTH SYSTEMS

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ABSTRACT

MIAO JIANG: A Discrete-Event Simulation Model of the U.S.
Juvenile Justice and Mental Health Systems
(Under the direction of E. Michael Foster)

Juvenile crimes have serious consequences for individuals, families, and society as a whole. Youth in the juvenile justice system may have complex mental health needs that require coordination of multiple systems. Oftentimes those needs are not adequately addressed because resources are limited, and care, fragmented. In recent years, many community-based rehabilitative approaches have been identified, some showing positive outcomes associated with reduced long-term recidivism, improved family functioning and school performance.

Despite the potential benefits of those interventions, key system questions remain unanswered. For example, what capacity is needed to deliver the interventions? What effect would they have on the crime in a community as well as on the life course of young offenders? No single economic study can completely assesses all of the key questions surrounding complex systems like these.

This article presents a discrete-event simulation model that simulates youth passing through the juvenile justice system, mental health system, and the community. Drawing data from multiple sources, the model links quality of the mental health screening tool, access to treatment, service use, criminal outcomes, and service capacity together and assesses how various policies decide and are being shaped by the dynamics between various system

features. The results provide insight for policy makers to allocate constrained resources while maximizing the public health benefits of the programs. Meanwhile, the model demonstrates an innovative approach to integrate existing evidence and evaluate the economic impact of policies regarding mental health in juvenile justice.

To my parents, Weiyi Jiang and Jianhua Guo

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CHAPTER 1 INTRODUCTION

Research has documented high rates of mental health problems, learning disabilities, and substance abuse among youth in the juvenile justice system than those in the general population.[1-5] The care and treatment of youth with mental illness in the juvenile justice system requires coordination of multiple systems, including juvenile justice, mental health, education, and child welfare system. However, resources in those systems are often limited, and care, fragmented. In recent years, many community-based rehabilitative approaches have been identified, some showing positive outcomes associated with reduced long-term recidivism, improved family functioning and school performance.

Economic analysis is a key in examining the potential benefits and costs of those interventions. Cost-effectiveness analysis (CEA) provides a valuable tool for that purpose. CEA refers to the comparison of two or more treatments in terms of the incremental cost and benefits of one relative to the other(s). Such analyses provide insight for policy makers to allocate the constrained resources while maximizing the health benefits of the programs. It is well suited for examining the mental health treatment, which usually has limited resources.

One of the most commonly used analytic techniques in CEA is the decision tree. However, decision tree is difficult to handle population heterogeneity or tackle problems that are chronic in nature. It also cannot capture the dynamic of various decisions. In recent years, computer simulations in health care are growing in popularity and have been increasingly used in CEA. One such tool is discrete-event simulation (DES), which originated from the field of operations research and industrial engineering. DES models individual entities and links human characteristics like age, gender, disease history to those entities. DES model parameters are probabilities (or rates) that can be obtained from operational data or literature. In addition, the model is flexible enough to account for randomness, variability, and uncertainty that are inherent in mental health and juvenile justice systems.

This study will apply DES tools to model the passage of youth through the juvenile justice system, mental health system, and the community, and to evaluate the impact of various policy scenarios on the crime in a community. Ultimately we will examine two policy issues: 1) adding a community-based treatment program targeted at addressing youth's risk behaviors in the social context; and 2) the property of an imperfect screening tool for classifying youth into different risk categories at judicial intake. The model will link quality of the screening tool, access to treatment, service use, criminal outcomes, and system capacity together and assess how the above policies decide and are being shaped by the dynamics between various system features. Such analyses will provide decision support for policy makers in designing policies regarding juvenile crime prevention as well as mental health treatment of justice-involved youth.

This dissertation is organized as follows: chapter two provides background and significance of the study; chapter three describes the methodology used for the study; chapter four presents the findings; and chapter five provides a summary of the entire study, the public health implications, study limitations, recommendations for future research, and conclusions.

CHAPTER 2 BACKGROUND AND SIGNIFICANCE

This chapter starts with the history and prevalence of the mental health problems in the juvenile justice system. It then describes the emerging community-based treatments as an alternative to the costly residential services, and the problems with evaluating these treatments in cost-effectiveness framework. Following that, the chapter compares the discrete-event simulation tools with other economic evaluation tools and points out several advantages of the DES tools in the context of examining mental health policies in juvenile justice. The chapter concludes with the specific aims and the significance of the study.

2.1 Prevalence and Consequences of Juvenile Crime

Juvenile crime (exchangeable with juvenile delinquency in this context) broadly refers to status, minor, and serious offenses committed by youth under age 18. From 1998 to 2007, the total number of juvenile arrests has dropped by 20%, including a 14% drop for violent crimes, and a 33% drop for property crimes.[7] Although the decline in arrest rate appears encouraging, a significant number of youth still entered the juvenile justice system. For example, in 2007, an estimated 2.18 million juveniles were arrested, accounting for 16% of all violent crime arrests and 26% of all property crime arrests. Youth under age 15 accounted for more than one fourth (28%) of all juvenile arrests for violent crimes and one third (31%) of those for property crimes.[7] In addition, of all the violent crime indexes, juvenile arrests for murder actually increased 3% in 2006-2007.[7]

The social cost of juvenile crime is enormous. The typical criminal career over the juvenile and adult years costs society around $3.2 to $5.7 million (in 2007 dollars, not discounted).[8] Accounting for drug use and high school dropout associated with delinquency, the total societal cost of a high-risk youth may be as high as $4.2 to $7.2 million.[8] These costs were largely borne by the taxpayers, insurers, and other members of the society.
In addition, research has consistently found that a small group of youth ("chronic offenders") accounts for a substantial portion of all offenses, and they tend to have early onset of problem behaviors that continue into adulthood with more serious criminal activities.[9-11] As a result, the potential benefits of early prevention and effective treatment of juvenile crime are enormous.

2.2 Juvenile Justice System Overview

The juvenile justice system handles the majority of juvenile delinquent cases. The first juvenile court was established 110 years ago in Cook County, Illinois. Within the following 25 years, most states had set up their own juvenile justice system. States vary enormously regarding the structure, process, and service provision of the juvenile justice systems.

The early juvenile justice systems differed from the adult criminal system in several ways. [12] For example, it views the youth's problem as rooted in his or her family and social context. The emphasis, therefore, is more on diversion and rehabilitation than punishment. As a result, social workers instead of police handle those cases. Court procedures were informal, and the judges were to act on the child's best interest when making a decision regarding the case. In addition, the court proceedings were not open to the public and the records remained confidential. Finally, even the language used in juvenile court was different. Instead of being charged with crimes, found guilty, or sent to prison, the children were charged with delinquencies, adjudicated delinquent, and sent to detention center or training school.

Since the 1960s, a series of changes have taken place in the juvenile justice system. In particular, people are increasingly concerned about offender accountability and public safety with the surge of juvenile crimes in the 1990s. As a result, the juvenile justice system has been leaning towards a more punitive approach. For example, many states have lowered the minimum age limit of transferring youth to the criminal system for trial. Whether rehabilitative or punitive approaches work better in controlling juvenile crime is an ongoing policy debate.

2.3 Mental Health in the Juvenile Justice System

Mental illness broadly refers to all diagnosable mental disorders, such as affective disorders, anxiety disorders, disruptive behavior disorders, substance use disorders, and psychosis. The prevalence of mental illness among youth in the general population is approximately 20%.[1] However, the prevalence for youth in the juvenile justice system may be three or four times higher and varies by gender, race and age.[2-5] In particular, results from a multi-state, multi-system study funded by OJJDP have shown that the majority (70.4%) of youth in the juvenile justice system meet the criteria for at least one mental health disorder; among them, 60.8% also met criteria for a substance use disorder; and comorbidity (co-occurring mental health conditions) is substantial in this population.[5] In addition, 20% to 25% of youth in the juvenile justice system has serious mental health problems (disorders that result in functional impairment affecting family, school, or community activities).[3, 5]

Furthermore, a large proportion of these mentally ill youth were detained for relatively minor, nonviolent offenses. [13]

These mentally ill youth should receive appropriate treatment while detained, but few do. Although to date no causality has been established between mental illness and juvenile delinquency, growing evidence suggests that mental health and substance abuse disorders contribute to youth's delinquent behaviors.[14-20] However, due to capacity constraint, the care and treatment for these youth are often neglected. Research shows that of those who revealed significant depression and substance abuse problems, only a small percentage were provided medication or access to services.[21-23] When they do receive residential services, these services tend to be more costly than community-based services and are associated with higher rate of recidivism.[24, 25]

Youth are even less likely to have their mental illness treated in an integrated manner with timely and comprehensive services.[26] The juvenile justice and mental health systems generally reside in different agencies at the state level, and may even be administered at different levels of government. Their primary purpose in handling the youth entering the system differs—the former more of punishing bad behaviors while the latter more of alleviating psychiatric symptoms. no clear guideline regulate which system is responsible for serving these justice-involved youth with serious mental illness. As a result, a child may be passing back and forth between the systems without receiving adequate care.

2.4 Alternative Rehabilitative Approaches

Recognizing the complex needs of juvenile offenders and the fragmentation of the existing systems, many community-based rehabilitative approaches have been developed in recent years. They focus on addressing youth' behavior problems within their social and familial context, and emphasize the importance of providing continuum of treatment options by multi-system collaboration. Multisystemic Therapy (MST) is one such example. It is an intensive family-based treatment model targeting on youth with serious behavioral problems and emotional disturbance.[27] The treatment team consists of 3 to 5 master- or doctor-level therapists and crisis caseworkers. They work closely with the youth and the family to provide time-limited (3-6 months) services addressing the specific needs of the family, including connecting them with other social systems. The therapists have a small caseload (usually no more than 5 cases) and are available 24 hours a day and 7 days a week. For details about the clinical procedures of MST, see Henggeler *et al.*[28].

Extensive research has examined MST's efficacy and effectiveness. A recent review summarizes research on MST, including those from independent researchers.[29] Specifically, MST consistently reduced short-term and long-term (up to 14 years) recidivism, reduced rates of out-of-home placements, decreased substance use, decreased behavior and mental health problems, and improved family functioning (In Henggeler *et al.*[29] p270).

Research also demonstrated the cost-effectiveness of MST model. Aos and colleagues conducted an economic evaluation of the interventions for reducing crime, and MST has shown a net gain of $21,863 (in 1997 dollars) per participant for the taxpayer and victim costs avoided.[30] In 2001, they updated their meta-analytic methods and found that MST on average reduced recidivism by 31%, with a net gain of $131,918 (in 2000 dollars) per participant for the taxpayer and victim costs avoided.[31]

2.5 Unanswered Key System Questions

Given the high social cost of juvenile crime and increasing concern about the unmet mental health needs of youth in the juvenile justice system, researchers and policymakers have developed a comprehensive model to provide guidance in developing strategies, policies, and services in the field.[13] The model established four cornerstones that reflect the most critical areas of improvement—collaboration, identification, diversion, and treatment—upon which a series of key intervention points are identified, such as initial contact with law enforcement, intake, detention, judicial processing, dispositional alternatives, and re-entry.[13] MST has been mentioned as a promising practice in areas such as collaboration, diversion, treatment, judicial processing, dispositional alternative, and re-entry.

However, looking through the MST outcomes evaluation literature, one finds that in order to implement the approach into any community, some key system-level questions are left unanswered. For example, no study has considered the effect of limited service capacity of MST and the indication of that for the crime in a community. In addition, most studies (except one) follow participants in a short period of time and it is unclear what the long-term effect of MST will be. Furthermore, most studies examined a snapshot of the juvenile offenders without considering the life history of the offender's criminal career. Finally, the communities where MST is implemented are inherently different and we need a way to account for this heterogeneity. In summary, the majority of the existing studies about MST or any other model treatment programs are micro-oriented but we have many system-level questions left unanswered.

2.6 Discrete-Event Simulation Tool in Economic Evaluation

Cost-effectiveness analysis (CEA) framework provides a valuable tool to assess the above questions. These analyses compare alternative programs in terms of their incremental cost and benefit, and inform policymakers about the best way to allocate the constrained resources while maximizing the public health benefits of expenditures on those interventions.

Ideally, people need to conduct a well-designed economic study with patients being randomized into experiment or control groups. These patients are then followed for a long time to collect the key outcomes. In reality, such a study is costly and impractical because no study is comprehensive enough to forecast all the key questions surrounding a complex system, and it takes a long time before the study can produce any result and many other things may have happened during this process. For those reasons, people turn to decision-analytic techniques for solution. Such techniques link health status to risk factors, service use and costs, as well as to interventions.

One commonly used technique is the decision tree. It is a tree-like graph depicting decisions and possible consequences with probabilities, cost and utility. Although straightforward to compare the expected utility and cost across alternative treatments, decision tree is difficult to tackle chronic problems. In addition, it does not address the issue of population heterogeneity.

In recent years, computer simulation models have become more popular in public health studies. Simulation broadly refers to the imitation of the operation of a real-world process or system over time, mostly through a computer model of the underlying processes.[32] Common features of those computer simulations include drawing data from multiple sources, modeling a hypothetical cohort of people moving through the system, and linking health states, risk factors, service use and costs, and interventions together. Examples of such approaches include Markov model, system dynamics (SD), and discrete-event simulation (DES). Markov model assumes a hypothetical cohort of people who end up in one of the many mutually exclusive health states after each specified follow-up period following the transition probability matrix. SD uses feedback loops, accumulation of flows into stocks, and time delays to examine the behaviors of a complex system over time. The model is continuous, static, and deterministic in nature. DES, on the other hand, models individuals passing through the system whose state changes at the discrete time points. It is essentially discrete, dynamic, and stochastic modeling of a system.

With so many tools at hand, one needs to choose the most appropriate approach for his problem. Brennan and colleagues provide guidance for choosing the appropriate model structures under specific requirements.[33] Their choice of modeling depends on the nature of the economic evaluation, the features of the system under study, and the evidence available. Specifically, one needs to consider things such as population level, interactivity between agents, treatment of time and space, resource constraint, agent autonomy, and flexibility.

Based on the above list and the key system-level questions we want to examine, DES model is well suited for examining our research question for several reasons. First, we want to consider service capacity. And DES provides a way to incorporate resource constraint, while no other simulation approaches we mentioned before can do that. Second, DES can model time horizon and ageing process more flexibly than other approaches, which allows us to examine the long-term effect of any interventions on a community. Third, DES can pass multiple cohorts through the system, each having their own characteristics. This enables us to assess the effect of population heterogeneity. Finally, DES can model more complicated systems and relationships than Markov models; and DES is more appropriate for modeling the juvenile justice and mental health systems than System Dynamics because those systems have inherent uncertainty, randomness, and variability underlying their processes and structures.

As there is no perfect tool, the disadvantages of DES involve the time- and resource-consuming process of conceptualizing, building, and verifying the model, the vast information needed to populate the model, and not getting the exact answers from the simulation runs. Despite all these, DES still represents a cost-effective approach in examining the issue of mental health in juvenile justice based on the above criteria of selecting the right approaches.

2.7 Prior Research

In healthcare settings, people have used DES tool to assess the cost-effectiveness of testing for thrombophilia,[34] depression,[35] diabetes,[36] or HIV.[37] Beyond the economic evaluation, DES has also been used to model the functioning of the emergency room, patient flows to hospital beds, or length of stay, to name a few. Gunal and Pidd provide a review of the literature on DES for performance modeling in healthcare for the past 30 years.[38]

Simulation modeling also has a long history in criminal justice research. The notion of simulation modeling was first introduced to criminal justice system in the 1960s by the Task Force on Science and Technology of the President's Crime Commission.[39] Since then, simulation has been applied in various areas, such as prison population forecasting, cost-effectiveness analysis, criminal career trajectory, and resource optimization.[39, 40] For a brief review of justice modeling history, see [39, 41-43].

Recently, a group of Australian researchers built a DES model of the Queensland juvenile justice system.[44, 45] Their model forecasts the finalized court outcomes and the reoffending behavior of the offenders to 2010. In addition, the model assists in decision-making by examining the trend after adding policy leverage points such as crime prevention, pre-court diversion and post-court interventions. The researchers simplified the complex system into a parsimonious model that captured the crucial components of the system as well as individual behaviors. The model provides a valuable tool for policy makers to analyze the medium-term impact of Queensland juvenile justice policies.[45]

This methodology, however, has not been used to examine issues involving mental health in juvenile justice setting.

2.8 Specific Aims

The primary aim of this dissertation is to build a DES model to simulate the passage of youth through different systems and examine the impact of various policy scenarios on the systems being modeled. The current project is more of a pilot study for a large-scale research project we are planning to undertake in the near future. Among the four cornerstones and series of intervention points mentioned in the comprehensive policy model, [13] we explore two in particular: treatment (dispositional alternative), and identification (screening). The prototype treatment in our model is MST, which targets at high-risk youth. Therefore, we also form our research question around the high-risk youth in our model.

Aim 1. To examine the impact of various policies of shifting resources between mental health and juvenile justice systems on crime in a community and the system-level performance.

The study examines several key outcomes at the individual and the system levels. Those include the utilization of the mental health treatment service, the unmet mental health needs in juvenile justice system, the percentage of youth who enter adulthood with multiple offenses (they are termed as “chronic offenders”), the percentage of youth who are classified as at high risk for reoffending, their average arrests, and finally, the cost of treating those at-risk youth via different options.

In addition, the study examines how the answers to the above questions depend on key parameters of the model. These parameters include: a) the capacity of the mental health treatment; b) the proportion of youth who are sentenced to receive the treatment; and c) the effectiveness of mental health treatment; d) the cost; and e) the operational features of the juvenile justice system (e.g., arrest rate, average stay in detention).

Finally, the study examines how the relationships between the key features of the systems and the model parameters change under alternative policy scenarios: a) send every youth to juvenile detention (unlimited capacity) regardless of his need for mental health treatment (baseline scenario); or b) send at-risk youth to receive community-based mental health treatment that has limited capacity.

Aim 2. To examine the relationship between an imperfect screening tool and the criminal career of juvenile offenders.

Each arrested juvenile has an underlying true risk status, which decides their rate of offending. On the other hand, the screening at intake identifies youth as in different risk categories, which decide their access to necessary services. When the screening tool is not perfect, the false-positive youth receives the services they don't need, while the false-negative youth misses the treatment. Under this aim, the study explores the relationship between the sensitivity and specificity of the screening tool, the prevalence of disorder among detained juvenile population, and the negative effect of the false positives and negatives on the recidivism rate.

2.9 Significance of Study

The proposed study provides an innovative approach to integrate existing evidence and model the dynamics of U.S. mental health and juvenile justice systems and the related policies. Meanwhile, it also advances the evaluation of juvenile crime prevention and mental health treatment more generally. First of all, researchers can use the current simulation models to analyze other policies, treatment, and interventions not considered here. Second, in the process of building and analyzing the model, sources of uncertainty can be identified, and their relative importance can be used to set priorities for future research. Finally, this model serves as the starting point to provide informed support for policymakers in making decisions about allocation of scarce public resources, coordinating various childcare systems in treatment justice-involved youth with mental illness, and planning short-term and long-term strategies for the juvenile justice and the mental health systems.

CHAPTER 3 METHODOLOGY

This section describes in detail how to simulate the juvenile justice system embedded with community-based mental health programs. Law outlines the general steps in a sound simulation study as 1) formulate the problem and plan the study; 2) collect data and define a model; 3) check whether the assumptions are valid; 4) construct a computer program and verify; 5) make pilot runs; 6) check whether the programmed model is valid; 7) design experiments; 8) make production runs; 9) analyze output data; and 10) document, present, and use results[46] (p.66-70). We start with a brief introduction of the basic concepts in discrete-event simulation, followed by a description of the software we use. We then use specific aim one to describe the major steps following the above guidelines, and comment on steps where specific aim two is different from specific aim one.

3.1 Discrete-Event Simulation Basics

As we mentioned before, discrete-event simulation (DES) is well suited for modeling the flow of delinquent youth through the juvenile justice system. There are some fundamental concepts in DES. These are outlined in the text box below. In our DES model, each individual is an "entity" in the language of DES. Their demographic information and arrest history are their "attributes". Characteristics of the system that are the same for all the entities, such as the prevalence of mental disorder among the detained youth or the capacity of the mental health facility are "variables". Mental health facility represents one type of “resource” and is of primary interest. When the mental health facility is full, youth may form a queue waiting for service.

As the simulation program runs, it collects key information. Statistical accumulators are built-in, such as the simulation clock, or the number of entities in a queue. But we also need to set up and maintain our own statistical accumulators during the simulation. For example, we need counters to record the number of children in different risk groups who have used the mental health services. Those statistical accumulators are used to calculate the output at the end of the simulation run.

Key Terminology in Simulation (extracted from [6])

- *Entities*--parts or people that move around and change status. They have to be created, and may be disposed or circulating in the system.
- *Attributes*--characteristics of entities, value is specific to that entity, like “local” variable.
- *Variable*—global values that reflect some characteristics of the system regardless of the entities.
- *Resources*—represent things used to provide service, usually with limited quantity, available in “units”, entity “seizes”, use, and “releases” the resource.
- *Queues*—place for entities to wait for resources to become available, the length of queue and wait time are two common performance measures.
- *Statistical Accumulators*—variables that collect the various intermediate measures as the simulation progresses, don’t participate, just watch.
- *Events*-things happen at an instant of time that might change attributes, variables, or statistical accumulators, such as arrival, departure, or the end of simulation.
- *Simulation clock*-a variable that holds the current value of time in the simulation, not continuous but event-based.
- *Starting and stopping*-the rules and assumptions about how to start and stop the simulation. These rules are translated into values for attributes, variables, accumulators, event calendar, and the clock.

As the name DES suggests, the simulation clock advances not in a continuous manner, but only at discrete point of time where an event happens. Such events include things like getting arrested, being sentenced, or being released from mental health treatment.

In addition, we need to decide how to start and stop the simulation run. If there is a natural initial condition and a natural stopping event, we are running a *terminating* simulation. Examples include simulation of a bank that opens in the morning and closes in the evening or a project being implemented with a time horizon of 12 months. In those instances, the initial conditions are considered part of the simulation and must be included in the output analysis.

On the other hand, we may be interested in the long-run behavior of a continuously running system. Then we are running a *non-terminating* (*steady-state*) simulation. In such systems, the initial conditions should not influence the long-run performance of the system, and the run is supposed to go indefinitely. In practice, because we cannot let the simulation run forever, and we do not know much about the system we are simulating ahead of time, what people tend to do is to let the system "warm-up" for a period of time until the effects of initialization likely wear off. Then the statistical accumulator starts to collect the data for the output analysis.

Our simulation is essentially a steady-state simulation as we are interested in examining the performance measures of the system and how we can improve those measures in the long run. Such information will provide valuable support for decision makers to plan budget and allocate resources more efficiently.

3.2 Software

Once we have set up the conceptual framework and decided the modeling strategy, we need to choose appropriate software to implement the conceptual model. We use Arena 10.0, a general-purpose simulation package based on SIMAN simulation language [6, 47]. Arena is built on modules, which are pre-programmed building blocks with specific functions. For example, each Arena model starts with Creation module, and ends with Dispose module, and one can put other modules in between.

Arena has several built-in functions, including input analyzer, process analyzer, output analyzer, and OptQuest. These functions play an important role in several key steps of simulation and have an effect on how we handle some substantive issues. We will provide more details where appropriate.

3.3 Specific Aim One

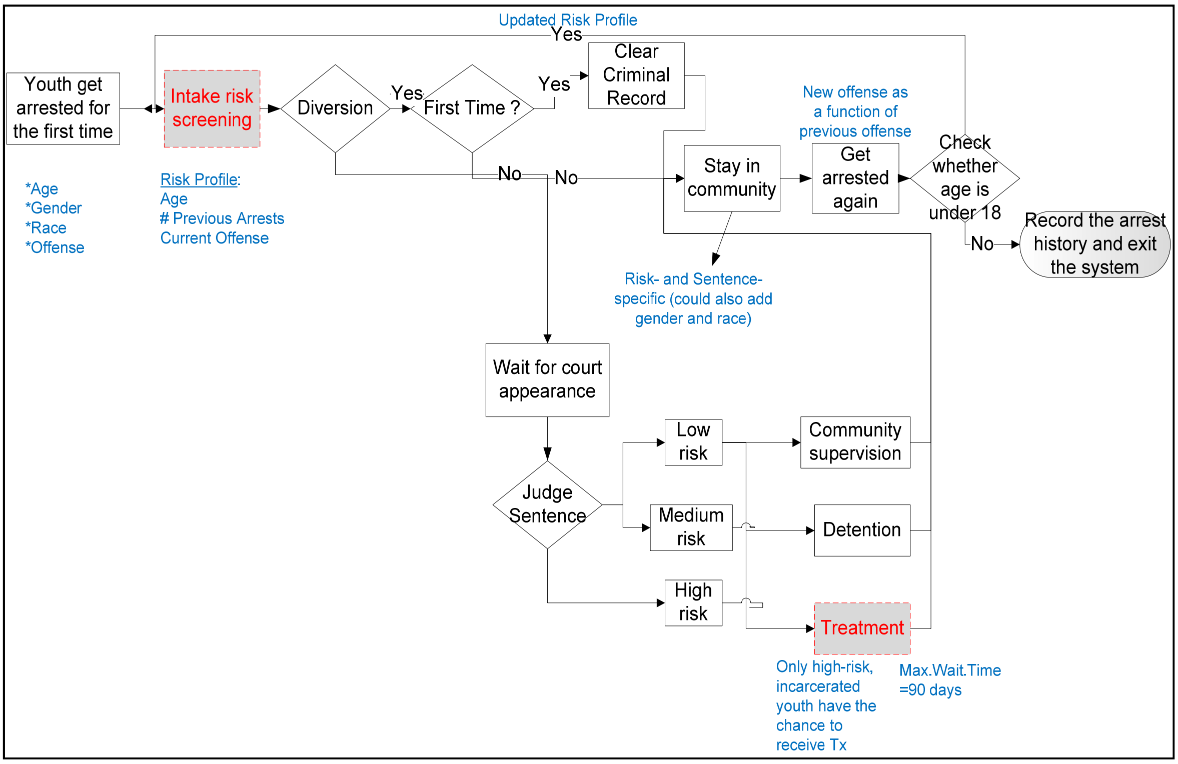
3.3.1 Problem formulation.

The objective of aim one is to assess the effectiveness and cost-effectiveness of adding a community-based mental health treatment targeted at youth with high-risk of reoffending. We assess this at different values of key model parameters, including the capacity of the treatment facility, the percentage of at-risk youth who are sentenced to receive the treatment, and the effectiveness of the treatment on reducing recidivism.

Figure 1 presents the broad, conceptual structure of the juvenile justice simulation model. This model is adapted from the Office of Juvenile Justice and Delinquency Prevention (OJJDP) flowchart (p.105).[48] The model captures the key features of the juvenile justice system we want to examine in specific aim one. It is essentially a series of decision points within the juvenile justice system. Meanwhile, this representation incorporates the policy levers of interest, i.e., screening for high-risk youth at intake and providing community-based mental health services for those in need.

The model represents the experiences of youth ages 10-17 living in the community in the long run. These youth are at risk of offending and arrest. An individual enters the model when he commits a crime and gets arrested for the first time. Upon entering into the justice system, he undergoes an initial risk screening that essentially identifies him into one of the three categories: low, medium, or high risk. Such a risk status represents a combination of multiple factors that may predict his future arrest, including his age, mental health status, current offense, and the arrest history for a recidivist. We use this risk status as an indicator of the need for mental health treatment, which is targeted not only on treating psychiatric disorder, but also on addressing youth's anti-social behaviors and other problems.

Figure 1. Conceptual Framework for Aim One



Based on the screened risk status, the youth has different chance of being diverted out of the formal processing. If diverted, he returns to the community. If this is the first time he is diverted, he will have no criminal record. Otherwise, his number of total arrests and that of previous arrests are both increased by one.

If the youth does not get diverted and goes through formal hearing, he may be held in a secure detention center, waiting to appear in the juvenile court. At the hearing, the judges may sentence the youth to any of the two places based on his screened risk status: community supervision (analogous to probation), or detention a correctional facility. Among those who are sentenced to detention, the judge can make a second decision to either send them to detention or to receive community-based mental health treatment. The judge can also decide the proportion of the detained youth who should receive the treatment.

This point is where different policy scenarios can be incorporated. For example, we can examine one scenario where 100% of the high-risk detained youth receive treatment, and compare it with another scenario where only 50% of the high-risk youth who are sentenced to detention can receive the treatment. Here the proportion is a key element to control by the analyst. Another key control is the capacity of the mental health facility.

When the treatment facility is full, a youth may wait for treatment for up to 90 days in a secure facility. Beyond 90 days, if there is still no slot available for treatment, the youth is sent to detention. Doing so reflects the reality where one cannot wait indefinitely in a queue for mental health service. Meanwhile, it reflects the software requirement—Arena has a limit on total number of entities that can circulate without being disposed. And the 90-way waiting period enables us to run the model at reasonable length without keep too many entities in the model. One can also choose other waiting period that they deem sensible.

After serving his sentence, the youth returns back to the community and may become involved in the juvenile justice system again. At that point his age is checked and if he is 18 and beyond, he exits the current system with his arrest history recorded. Otherwise, he goes through the same process of diversion or formal hearing with his number of arrests updated.

The above elements of the systems, their relationships, logic, and the underlying dynamic processes are the basis for translating the conceptual framework into a computer model.

3.3.2 Model parameters.

The conceptual model allows us to examine how the structure of the system impacts the output measures of interest. To do this, one needs to specify features of the key model components. Those features describe the statistical processes and their associated parameters. DES model parameters generally fall into two categories, time-related (e.g., time spent in detention), or probabilities and proportions (e.g., prevalence of mental disorder among detained youth).

Table 1 provides a list of the model input parameters for specific aim one. We examine three in more detail: the proportion of high-risk youth who are receiving community treatment as the alternative to incarceration, the capacity of the mental health treatment, and its effectiveness on reducing subsequent crimes. Those are highlighted in gray in table 1.

Other parameters needed to populate the model include the demographic composition of the juvenile population in the community, the proportion of young offenders who are diverted out of the juvenile justice system, time the young offenders spent in various components of the model, and the costs associated with various procedures in the juvenile justice system.

The flexibility of this model to examine the policy questions lies in that one can choose any parameter and examine how the change in that particular parameter will affect the outcomes of interest. For example, instead of the controlled parameters mentioned above, one can choose the demographic composition of the juvenile population as the controlled parameter and assess how the delivery of the community-based rehabilitative services will vary depending on the community the program resides, whether it is a poor or rich community, having predominantly non-Hispanic White or African American, and having more girls than boys or vice versa.

3.3.3 Obtaining parameter estimates.

DES provides a way of synthesizing research evidence across studies. One can obtain estimates of the model parameters from prior research, analysis of existing data, as well as expert opinion. Prior research may take the form of clinical trials, observational studies, or administrative report, among others. For example, a series of reports from Washington State [31, 49-54] provides consistent figures regarding the juvenile offender population in that state. In addition, Multisystemic Therapy (MST) represents an evidence-based community mental health treatment. The program runs for more than 30 years and has published 15 outcome studies (14 randomized, one quasi-experimental).[55] These studies provide estimates of the average stay in mental health treatment and the effectiveness of the treatment on reducing subsequent crime. Other established studies also provide estimates such as the prevalence of mental disorder among detained youth.[2-5]

Meanwhile, where existing research does not provide estimates of relevant parameters, experts' opinion may be solicited. In our case, we contacted two main authors of the series of reports from Washington State and obtained their feedback on the conceptual model as well as the data we used in the model.

Obtaining high-quality data is the key to a successful simulation. We recognize and anticipate that the model parameters will vary widely in the amount of information available for estimating them. Those parameters for which little information is available will be

Table 1. Key Model Parameters for Aim One

Input Measure	**Description**
Youth get arrested for the firs time	Exponential (Mean) days
Demographic distribution of first-time offenders	Age and gender
Initial risk screening	A function of current age, current
Diversion%	Risk-specific
Waiting time in detention center	Exponential (Mean) days
Judge's decision making process	Risk-specific
Percentage of high-risk detention kids receiving mental health treatment [a]	Ranging from 0 to 100%
Percentage of med-risk detention kids receiving therapy	Ranging from 0 to 100%
Mental health facility capacity	ranging from 0 to 1000
Effectiveness of the mental health treatment	% reduction in recidivism
Time spent in mental health treatment	Triangle (min, mode, max) days
Time spent in community supervision	Exponential (Mean) days
Time spent in detention	Exponential (Mean) days
Stay in community after serving a sentence until next offense	Risk- and sentence-specific
Cost associated with diversion process	per session
Cost associated with community supervision process	per session
Cost associated with detention process	Annually
Cost associated with mental health treatment	per session
Output Measure	
System-level	**Individual-level**
Total cost	Average number of arrests for chronic offenders
Cost for high-risk youth	
Percentage of chronic offenders entering into adulthood	Average number of arrests for chronic high-risk offenders
Percentage of high-risk offenders entering into adulthood	
Percentage of high-risk kids among chronic offenders	
Utilization of mental health facility (percentage of resource being busy)	
Total number of children served by mental health facility	
Proportion of children with unmet mental health needs	

[a] Those highlighted cells are the parameters we want to test in different values

associated with low precision. This may be reflected by using a distribution for the parameter with a wider range. A key part of the methodology, therefore, is to assess how sensitive the key model performance measures are to the model specifications. We assess several key model parameters in sensitivity analysis section.

3.3.4 Input modeling.

Once we collect the data for the model parameters, we need to decide how to incorporate those data into the model. With existing data, one can use the historical data directly, or fit a probability distribution to the data. According to Kelton and colleagues,[6] there are tradeoffs between the two approaches. The historical data are true representation of the system one is simulating. But it only reflects what has happened in the past. On the other hand, sampling from a fitted probability distribution may smooth out chance events in the past and may predict better for the future, but it may also generate values that are impossible or lose important characteristics of the system.

With experts' opinion, one can translate that information into some commonly used distribution, trirangular distribution as an example. That distribution needs three pieces of information, the minimum, the maximum, and the most likely value. If no more detailed information can be obtained, one can at least seek experts' opinion about their experience on those values to put in the model.

Arena provides built-in tools to incorporate the above approaches by either embedding the data as part of the model data structure, reading the data dynamically during the simulation run, or fitting a probability distribution. Meanwhile, it also provides tools to check the goodness-of-fit. Example of such tools is discussed in Model Validation section. The choice of approach depends on the availability of the data, the computational speed, and the subject matter. Due to the nature of this research project and the time frame, we mainly obtained the parameter for a pre-assumed distribution from existing literature. In the near future, when we can have access to individual-level data, we may be able to employ other approaches mentioned above.

3.3.5 Output performance measures.

The performance measures that we use include cost, proportion, and the number of people. Specifically, system-level performance measures include the average cost per each juvenile offender, the average cost of treating high-risk youth, the total number of chronic offenders and that of high-risk youth generated from the system, the percentage of chronic and/or high-risk offenders, the mental health service utilization, and the proportion of children who goes to detention due to the capacity constraint of the mental health treatment. Individual-level measures include the average arrests and the average time to recidivist for a high-risk and/or chronic offender. Table 1 also provides a list of key model output parameters.

3.3.6 Model assumptions.

The conceptual model lays the foundation for the simulation modeling. When implemented in a computer program, the model requires assumptions about the dynamic processes underlying it. These assumptions reflect existing research or well known features of the systems involved. In some instances, the assumption has specific conceptual implications, and in those cases we comment on those.

These assumptions may involve not only specific values of the parameters but also distributional assumptions or mathematical functions. For example, the generation of new offenders entering the juvenile justice system is assumed to conform to an exponential process. This means that the rate is constant during the period the model simulates. One can also find other ways to model this process, such as generating batches of children entering the model at different time where the batch size can be fixed or varied.

Key Model Assumptions for Aim One

- Juvenile is defined as children age 10 to 17
- The initial and ending condition of the model does not matter (steady-state)
- The first-time offending follows an exponential distribution
- The screened risk status is a categorical measure as the function of age at offense, nature of the offense, and the number of previous arrests
- When a youth is released or gets arrested again, his age is checked and if he is older than 18, he exits the system
- Each time the youth is arrested, his number of total arrests is updated only when he is less than 18.
- If a child receives diversion for the first time, he is considered being released back to the community without any arrest record
- The judges make decision based on the risk status of the offenders at screening
- The capacity of the mental health facility is limited and high-risk kids have priority over medium-risk kids
- If a kid has been waiting for 90 days to receive the treatment and the facility is still full, he goes to detention
- No high-risk kid gets diverted out of formal hearing or is sentenced for community supervision
- No low-risk kid gets sentenced to receive community-based treatment
- The capacity of the residential placement is unlimited
- The recidivism depends on the child's risk status and his last disposition
- The time to next offense follows an exponential distribution
- Community treatment is at least as effective as the residential placement, or even better
- The new offense committed by a recidivist is based on the previous offense, and this relation holds for both first-time recidivist and repeated recidivist.
- If a new offense is not committed in the same category as previous offense, the new offense is equally likely to be in the rest of offense categories
- The ratio of all-type recidivism across risk levels is the same as it is for felony recidivism

Many of the assumptions reflect well-known characteristics of the juvenile crime. For example, data show that the probability of committing a crime and getting arrested is really small for children under age 10, and it varies with age.[56] Therefore, we define our study population as children between 10 and 17 and the risk of offending as age-varying. Other assumptions represent the features of the juvenile justice system, such as allowing a proportion of youth being diverted out of the system—that is, returned to their parents without a court hearing. Still other assumptions are simplified representation of the juvenile justice system in real world. For example, in aim one, we use three risk categories (high, moderate, and low) to reflect the combination of multiple factors including the youth's age at offense, his mental health status, the nature of the crime he committed, and the arrest history. Finally, some assumptions originate from the nature of the policy questions of interest—such as set a capacity limit for the mental health facility as well as set priority for allocating such costly resources.

This level of detail is consistent with the overall goal of the simulation, namely, to see whether community-based mental health treatment *works* or *not.* If later, we want to examine whether there is a specific type of disorder that the treatment works *best*, we can go back and add detailed diagnosis of the disorder into the model. Note that future models may also relax some of these assumptions. A key strength of simulation modeling is that the complexity of the modeling is limited only by (1) computational capacity; (2) the availability of data necessary to specify relevant parameters; and (3) ones imagination of knowledge of the systems involved.

3.3.7 Data source.

In this section, we provide more details about the data source we use to populate the model and how we obtain several key parameter estimates from those data. Because juvenile justice systems in this country are so diverse, we try to use data from the same juvenile population as close as possible. A series of reports from Washington State [31, 49-54] provides us consistent figures regarding the juvenile offenders in that state. Where there is no relevant information available for Washington State, we use figures from other sources.

3.3.7.1 Juvenile population in Washington State.

There were a total of 710,550 juveniles in Washington State as of fiscal year 2005. More than half were males, and more than two thirds were non-Hispanic White. There were a total of 13,127 sentences in the juvenile justice systems in that year, 3,190 first-time offenses and 9937 recidivist. More than three fourths of those sentences were committed by males. African American juveniles accounted for only 4% of the population but 13% of all the sentences. Asian American and Pacific Islanders, on the other hand, accounted for 6% of the population but only 3% of the sentences. Table 2 provides the demographic information of this population.

Table 2. Demographics for the Juvenile Population in Washington State Fiscal Year 2005

	Juvenile Population	% of Juvenile population	First-time Sentences	% of First-time Offenders	Recidivist	Total Sentence	Recidivism rate
Gender							
Female	346,001	48.75%	820	26%	2,133	2,953	72.23%
Male	364,549	51.25%	2,370	74%	7,804	10,174	76.71%
Race/ Ethnicity							
African Am.	27,671	3.94%	366	11%	1,303	1,669	78.07%
Asian/Pacific Islander	43,865	5.98%	132	4%	246	378	65.08%
Caucasian	513,491	69.23%	2,033	64%	6,145	8,178	75.14%
Hispanic	79,450	13.71%	323	10%	1,501	1,824	82.29%
Native American	13,875	5.29%	140	4%	480	620	77.42%
Total	710,550		3,190		9937	13127	75.50%

Among the first-time offenders, more than half are between the age of 15-17, followed by 21% at age 14, and 14% at age 13. According to the report,[50] the average age of first-time offenders is 15.13. Table 3 provides the age distribution of the juvenile offenders.

More than half of the offenses committed by first-time offenders are misdemeanors, and 14% of them are violent felonies (assault, murder, manslaughter, robbery, and sex offense). The rest are non-violent felonies (drug, property, and other offenses). Table 4 provides number of juvenile offenders by offense types.

Table 3. Age Distribution of the Juvenile Offenders in Washington State Fiscal Year 2005

Age	First-time Offense	First-time Offender Percentage	Recidivist	Total
<10	4	0.13%	5	9
10	16	0.50%	13	29
11	68	2.13%	29	97
12	238	7.46%	204	442
13	455	14.27%	682	1150
14	681	21.35%	1,533	2214
15-17 [a]	1727	54.15%	7,464	9192
Total	3189	100.00%	9930	13120

[a] Divided between age 15, 16, and 17 by 20:24:35 ratio according to [b]

[b] Juvenile Violence in Washington: First-time and Repeat Offenders (1996)

According to another Washington State report based on a cohort of 92,967 first-time juvenile offenders who became 18 years old between 1988 and 1994,[52] 76% of them were diverted out of formal judicial processing, 15% of them were sentenced to community supervision, and only 9% of them were sentenced to detention. Table 5 provides number of juvenile offenders by disposition.

Table 4. Juvenile Offenders by Offense Types in Washington State 2005

	First Time Offender	Recidivist	Total	First-time%	Recidivist %
Misdemeanor	1,749	6,869	8,618	55%	80%
Non-violent felony [a]	979	2440	3419	31%	71%
violent felony	450	580	1030	14%	56%
Total	3,178	9,889	13,067	100%	

[a] Include drug, property, and other offenses

[b] Include assault, murder, manslaughter, robbery, and sex offense

The information above serves as the basis for our creation of the first-time offenders in the model.

Table 5. Juvenile Offenders by Disposition in Washington State 1988-1994

	Diversion	Community supervision	Detention
Misdemeanor	67476	5070	836
Non-violent felony	3551	8085	6356
violent felony	0	549	1044
Total	71027	13704	8236
Proportion	76%	15%	9%

3.3.7.2 Juvenile justice system in Washington State

Washington State provides juvenile delinquency services at both the state and local level. Local courts administer probation and detention services, except in four counties. The Department of Social and Health Services, Juvenile Rehabilitation Administration (JRA), administers commitment programs and aftercare (i.e., parole). Below we list features of the juvenile justice system in Washington State that are relevant in our model. The source for this information comes from the State Juvenile Justice Profiles website.[57]

Delinquency intake screening. Upon receiving and reviewing all juvenile delinquency referrals made by law enforcement, the prosecutor decides the charges to put on against the juvenile and whether the offender will be handled formally or informally.[57] The screening tool they use is the Washington State Juvenile Court Assessment (WSJCA). This is a two-stage, 132-item assessment developed by the Washington Association of Juvenile Court Administrators and the Washington State Institute for Public Policy.[53] The pre-screen assessment is to quickly indicate whether a youth is of low-, moderate-, or high-risk to reoffend based on a combination of the youth's criminal and social history scores. The full assessment is administered only to those rated as moderate- and high-risk at pre-screen. This assessment forms the basis for assigning juvenile offenders to the state-funded research-based programs, such as Functional Family Therapy or Multi-systematic Therapy. For example, one has to be at moderate or high risk with a Family Dysfunction Scale of at least 6 out of 24 points to be eligible to receive FFT. Similarly, one has to be at high risk with high family risk factors to be eligible to receive MST.[53]

Diversion. First-time offenders referred for misdemeanor offenses are eligible for diversion. This involves, among others, a diversion intake interview with the youth and his or her parents, and a diversion agreement that may include restorative justice options such as community service or education program.

Probation supervision. Juvenile offenders assessed as being moderate and high risk to reoffend are assigned to juvenile probation officers' caseloads. For offenders in some categories, such as sex, substance abuse, or mental disorder, they may receive specialized services corresponding to the needs of the offenders. This usually includes a placement on community supervision for a period of time (e.g., a minimum of 24 months for sex offenders), and other education or treatment programs.

Detention and JRA. Youth may be held in a detention facility either before adjudication, or as a disposition. For pre-adjudication detention, it is warranted under situations where a youth is unlikely to appear for future proceedings, or where detention is necessary to protect the juvenile, the community and/or witness. Meanwhile, youth can also be sentenced to incarceration at a local detention facility for a maximum of 30 days. If the youth committed serious crimes or has an extensive criminal history, he or she may also be sentenced to incarceration averaged between 30 to 47 weeks in state institutions managed by the Juvenile Rehabilitation Administration (JRA).

Treatment. The state implements many evidence-based treatment programs targeting at youth who are at moderate- or high-risk for reoffending. Examples of such programs include Multisystemic Therapy (MST), Functional Family Therapy (FFT), and Aggression Replacement Training (ART).

The above summarizes the key features of the juvenile justice system in Washington State. These features are not exactly the same as those in our conceptual model. We use their information where it is relevant.

3.3.8 Key model parameters.

In this sub-section, we illustrate how we obtain estimates of several key parameters for aim one from various data source. Appendix A-F provides more detailed description of the Arena model specification for aim one.

3.3.8.1 Initial rate of entering into the system.

According to table 2, a total of 3,190 new offenders entered into the State of Washington juvenile justice system in fiscal year 2005. Assuming an underlying exponential process, the rate is calculated as:

365.25/3190=0.114 (every 0.114 day a new first-time offender enters into the system). [1]

3.3.8.2 Recidivism rate for offenders after diversion.

Based on data from Multnomah County in Oregon, [58] 21% of the youth who have been handled only informally had at least one new criminal referral within 12 months.

Again, assuming an exponential process for recidivist activities $f(t,\theta)= \theta\exp(-\theta t)$, if ρ of the group experienced the event by time t, then $\theta_{Diversion}=-\ln(1-\rho)/t=-\ln(1-0.21)/365=1/1548$.

[1] We use this rate in the model for pilot runs and found that after running for a certain time (2000 days) the entities in the system exceed the limit Arena puts for academic version. Given that we are running steady-state simulation and the initial condition of the system should not matter, we increase this rate to 0.2, and that solves the problem about the entity limit.

The interpretation is that a youth who was handled informally on average waits for 1548 days before he/she commits another criminal activity that gets him/her arrested again. Normally only the offenders in the lowest risk level will go through this informal process.

3.3.8.3 Recidivism rate for offenders after community supervision.

Based on one Washington State report,[49] the 36-month multivariate-adjusted recidivism rates for all measures for the parole groups was 78% for cohort 1, and 72% for cohort 2. Therefore, the average of the parole groups is (78%+72%)/2=0.75. Then

$\theta_{CommunitySupervision}=-\ln(1-\rho)/t=-\ln(1-0.75)/(36*30.25)=1/786$

This group includes all but the highest risk and sex offenders. So the risk level is medium.

3.3.8.4 Recidivism rate for offenders after incarceration.

Based on data from an independent MST outcome study, [59] the 18-month recidivism rate for MST group is 66.7%, that for comparison treatment-as-usual group is 86.7%. Because treatment-as-usual provides minimal supervision and treatment after incarceration, we use the recidivism rate for this group as the one for incarceration.

$\theta_{Incarceration}=-\ln(1-\rho)/t=-\ln(1-0.867)/(18*30.25)=1/270$

These youth are eligible for study inclusion if they are convicted of felony and they are sentenced to incarceration. Therefore, they belong to the high-risk level.

3.3.8.5 Recidivism rate for offenders receiving MST.

Using data from the same MST outcome study above, [59] and define α as percent reduction in recidivism as compared to the detained youth, we also calculate a formula for average community stay after MST treatment for high-risk youth

Exponential $(-18*30.25/\ln(1-(1-\alpha)*0.867))$.We can then vary the level of effectiveness to see its impact on the output measures.

3.3.8.6 Recidivism rate for offenders at different risk level.

Based on a report assessing the screen tool for the Washington State juvenile court, [53] the 18-month felony recidivism rate is 11.2% for low-risk level, 20.6% for moderate-risk level, and 32.2% for high-risk level. The ratio for average stay in community following an exponential distribution, is ln(1-0.322):ln(1-0.206):ln(1-0.112), which equals to 1:1.88:3.02. Assuming this ratio for felony recidivism also holds for the overall recidivism, we can fill in the values for the recidivism table, which is risk- and disposition-specific. For example, we know the average stay for low-risk youth after diversion is 1548 days, that for moderate-risk, using the above ratio, is going to be 823 days, and that for high-risk youth is 513 days (although the chance of getting diversion while being screened as moderate or high risk is really small). Appendix B.5 provides detailed figure for this parameter.

3.3.9. Model verification and validation.

3.3.9.1 Model verification.

Model verification refers to the correct implementation of a model into computer programs or simulation software.[60] This task mostly involves debugging the error messages generated from the Arena model and fixing them. Such errors may be due to data input, initialization, unit of measurement, arithmetic errors, or language conceptual errors, just to name a few. Arena has many features that help smooth this process, such as error checking, trace, break, watch, and animation. We have employed those techniques to make sure the model runs smoothly and generates reasonable output.

3.3.9.2 Model validation.

Model validation refers to checking whether the simulation model can reproduce the real system under study.[6] The focus is on conceptual validity and operational validity.

Conceptual validity is related to validation of the conceptual framework. Assessing this feature requires a close interaction with the subject-matter experts on justification of the simulation objectives, model assumptions, constraints, etc..

Operational validity involves testing whether model-generated data are characteristics of the real-world system behavior. As Law [46] suggests, quantitative techniques should be used whenever possible to test the validity of the model components. For example, one can use goodness-of-fit tests accompanied by graphical plots to assess whether a fitted probability distribution adequately represents the set of observed data. Or as another example, if several sets of data are used to describe the same "random" component, the Kruskal-Wallis test of homogeneity of populations can be used to see if one can merge the data into a combined set.

Operational validation has three aspects. The first aspect involves examining the parameters and relationships. For instance, one can increase the number of youths entering the juvenile justice system and see if the utilization of mental health services increases (or levels up if the capacity has already been full) as expected.

The second aspect involves determining which factor has a significant impact on the performance measures of primary interest. Such factors need to be handled more carefully. This is achieved through the sensitivity analysis. Law [46] (p.258) pointed out several things that can be investigated by a sensitivity analysis: the value of a parameter, the choice of a distribution, the entity moving through the simulated system, the level of detail for a subsystem, or deciding what data to be the most crucial to collect. This is where we can examine how the reliability of data source affects the output performance measures. Note that a key part of the sensitivity analysis is to use the method of common random numbers

(CRN). Otherwise, one can hardly tell whether the change in performance measures is due to the factor under consideration or to the randomness of the model. We will talk more about CRN in Output Analysis section.

The last aspect of operational validity involves comparing the performance measures of the simulation with past or existing systems, or expert opinion.[46] In our case, we do not have a past existing system. Therefore, we compare the simulated results with the literature or similar systems.

3.3.10 Design of experiments.

The primary goal of the simulation is to examine the effect of various juvenile justice policy scenarios on crime in a community. Design of Experiment (DOE) provides a systematic way to allow us to examine how changes to key features of the juvenile justice system impact the outcome measures. Experiment here means the execution of a computer simulation model; factor refers to the input parameters and structural assumptions; and response refers to the output performance measures.[46]

DOE provides an opportunity for system analysts to examine factors at their desired levels without intensive manual construction of each model one at a time. Such factors may be controllable in reality, or not. In either case, these experiments provide insights for making decisions about the implementation of the real-world systems. If a single factor is examined, that is the sensitivity analysis mentioned above. Often times, multiple factors are examined simultaneously and one wants to find the combination of those input-factors that optimizes the response of interest.

Table 6 provides the factors we examine in the experiment. Because simulation is not a simple sequential process but an iterative one, the factors and their levels employed here are meant to be illustrative, not exhaustive. If policy makers are interested in other factors or other levels, we can always go back to these steps and modify the model. The ultimate goal is to generate a response surface to predict the model response for system configurations that were not simulated due to time or cost considerations, and to find the combination of input-factor values that optimizes a response.[46]

Table 6. Design of Experiment

Control (Factor)	Base Case	Alternative Level
Aim One		
% Youth Diverted from Detention to Mental Health Treatment	0	20%; 40%; 60%; 80%; 100%
Mental Health Treatment Capacity	N/A	100; 200; 300; 400; 500
Percentage Reduction in Recidivism for Treatment	N/A	80%; 40%
Aim Two		
Sensitivity	100%	10% increment
Specificity	100%	10% increment
Prevalence of Disorder	0.7	0.3

DOE is implemented through Arena' Process Analyzer (PAN). PAN allows analyst to set up a series of scenarios by changing values of the model variables and resource capacities, and to choose the response from the model outputs. PAN is also embedded with graphic display of the results across replications and scenarios for comparison.

3.3.11 Output analysis.

To a large extent simulation involves experiments under a controlled environment. One cannot base his decision on a single simulation run because it only represents one realization of the true system under study and may have large variance. As a result, output analysis plays an essential part in understanding system behavior and generating predictions for it. Generally speaking, output analysis has three goals, 1) to design replication runs with the least computational cost for the most statistical information; 2) to estimate the performance metrics (obtaining point estimate and confidence intervals, etc..); 3) to design experiment to understand system behavior under various scenarios [61] (p165).

As we mentioned before, simulation can be classified into two categories based on their time horizon, terminating or steady-state. Each category has different statistical issues to deal with thus the output analysis also differs. Below we focus on the output analysis for the steady-state simulation as we are interested in the long-run behavior of the juvenile justice system. Arena's Output Analyzer, Process Analyzer, and OptQuest serve as the tools for conducting these analyses.

3.3.11.1 Warm-up and run length.

We want to examine the "behavior" of the system in its steady state, yet the system usually starts in empty-and-idle state, meaning no entities are in the system and all resources are idle. However, under the steady-state condition, entities have been created and are flowing through the system, and the resources tend to be busy. Including the data from the initial run may result in a bias on the steady-state system performance estimates. One solution to eliminate the bias due to initialization is to truncate some of the initial observations and start to collect statistics from then on. The difficulty, however, lies in determining the appropriate warm-up length as we often do not know the system we are simulating ahead of time. Generally, we let the model run for a long period of time and plot the performance measure we want the system to be stabilized on. Repeat this process for several times and examine whether the measure stabilizes across the replications. If multiple measures are of interest, people usually decide the warm-up length for each measure and choose the longest warm-up length for all the measures.

To better discern the points beyond which the system is stabilized, one can also follow Welch [62] to plot the moving average with different time widow sizes for a smoother curve (To do this, one must use other software rather than Arena). In any case, to be conservative, people tend to choose the truncation point larger rather than smaller. Another "rule of thumb" is that warm-up length generally takes less than 10 percent of the run length. So if the warm-up is about 5000 minutes, the effective run length should be at least 50,000 minutes (making the total run time 55,000 minutes).

3.3.11.2 Cost-effectiveness analysis.

There are several essential elements in CEA framework. The first one is the perspective of the analysis. Different perspective decides what costs to be included in the calculation. Generally speaking, CEA is conducted in a comprehensive societal perspective, that is, to incorporate all societal resources used in the program as costs and all effects as effects, regardless who pays for them and who benefits from them. Other perspective includes a "governmental" perspective, those of healthcare institution, third-party payer, or the patient and family. We adopt a societal perspective in this study.

Second, measures of cost and effectiveness are certainly an indispensable part of any cost-effectiveness analysis. We obtain the costing component of the model from the economic study of the interventions for reducing crimes in Washington State.[31] They estimate that the average cost of MST treatment per participant is $4,743 (p140); that of juvenile court intensive probation (comparable to community supervision in our model) is $2,234 (p146); that of diversion is $1,138 (p144); that of detention is $6,048 (weighted average of the local and state detention facilities, p83), all in 2000 dollars. Another report about Washington State juvenile courts workload and cost provides a different set of numbers. Measured as the average daily cost, diversion is said to cost $1.5, probation $5.28, and detention $93.26 per day (in 1995 dollars, and converted to 2000 dollars later).[63] We use the first set of numbers in the analysis and the second set in the sensitivity analysis. Table 7 provides the length of stay and costing estimates of the juvenile justice system.

Table 7. Length of Stay and Costing in Washington State Juvenile Justice System

Juvenile Justice System Component	Length of Stay (in days)	Total cost [a]	Daily Average Cost (in 1995 dollars) [b]	Daily Average Cost (in 2000 dollars)
Diversion	EXPO(63)	1,138	1.5	1.7
Community Supervsision	EXPO(205)	2,234	5.28	5.97
Detention	EXPO(183)	6,048 [c]	93.26	105.38
Mental Health Treatment	TRIA(30,120,180)	4,743		

[a] Aos S, Phipps P, Barnoski R, Lieb R. The comparative costs and benefits of programs to reduce crime version 4.0: Washington State Institute for Public Policy 2001.

[b] Washington State Juvenile Courts: Workloads and Costs. Olympia, Washington: Washington State Institute for Public Policy; 1997.

[c] Annual total cost.

Third, economists generally agree that in CEA, all future costs should be stated in "present value" to the decision maker to accommodate the differential timing of the costs occurred and the consequences on the effect side. There is ongoing debate about which discount rate one should use and whether the effects should also be discounted. In this study, we discount all the costs to the time the child was first arrested with an annual rate of 5% expressed in 2000 dollars. We do not discount the effects.

In CEA, one usually calculates an incremental cost-effectiveness ratio (ICER) interpreted as dollars spent per unit of desired outcome (e.g. increased quality life year), or bad outcomes averted (e.g. number of deaths prevented). The ICER is defined as:

$$ICER = \frac{Cost_{intervention1} - Cost_{intervention2}}{Effect_{intervention1} - Effect_{intervention2}}$$

As compared with cost-benefit analysis, which controversially translates the health outcomes into dollar amount, CEA requires fewer troublesome steps, and provides a coherent framework of comparing different interventions and preventions targeted at different population or diseases.

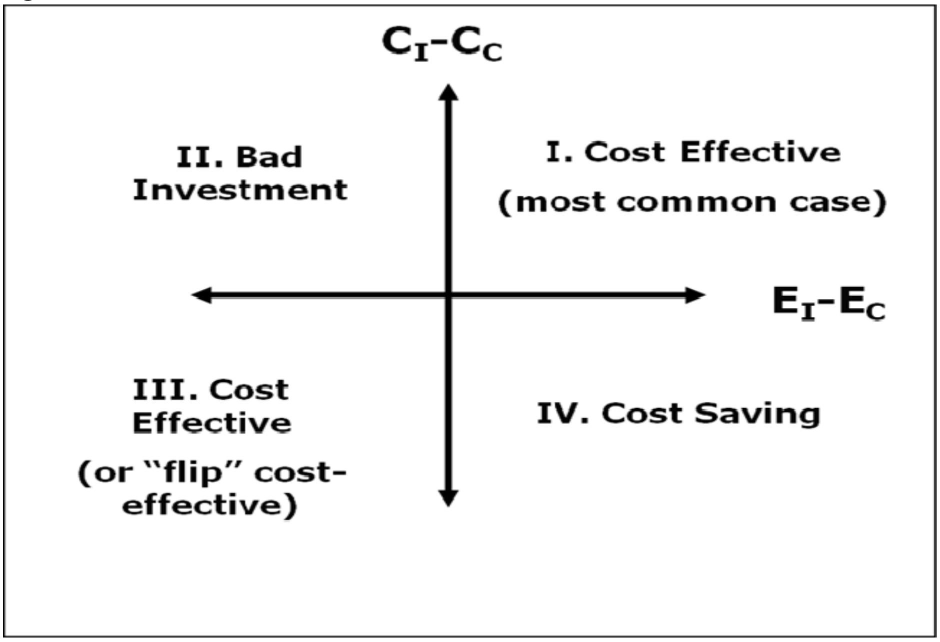
After calculating the ICER, one can plot it in CEA plane with incremental cost and incremental effectiveness as the axes and see if the intended program falls into the desired region. Figure 2 illustrates the CEA plane.

3.3.11.3 Comparing multiple systems.

We have multiple scenarios and this involves comparing multiple systems. In steady-state simulation, one can approach the problem in several ways. For example, one can decide a warm-up length and then run truncated replications. This way, we are making independent and identically distributed replications, which form a true random sample of the system under study.

Sometimes due to computational constraint, a simulation with long warm-up length can be very inefficient because each time the system has to discard so many observations. Then one can employ batch means method. In this method, one performs a really long run of a single replication. After the warm-up length, one can form dozens of batches and use them to compute a within-run sample variance. The key is to have enough observations and batch length so that the batch means are not heavily correlated. The method can be implemented by the analyst in Output Analyzer with more control over the number and size of batches. Or Arena will automatically calculate a batch mean with 95% confidence interval if the data pass tests of checking correlation among batches.

Figure 2. Cost-Effectiveness Plane



While the 95% confidence interval is calculated as

$$\bar{X} \mp t_{n-1,1-\alpha/2}\frac{s}{\sqrt{n}}$$

Arena usually reports half width $t_{n-1,1-\alpha/2}\frac{s}{\sqrt{n}}$ in its output section.

3.3.11.4 Common random number (CRN).

CRN is one particular variance-reduction technique to improve the precision of the result without inducing further computational efforts. As the name suggests, CRN requires using the same random number generator, seed, and streams for all alternative systems. Doing so introduces positive correlation between the systems, thus reduces the variance of the difference. This is achievable due to the "deterministic, reproducible nature of random-number generators" [46] (p579).

In addition, those random numbers need to be synchronized in the corresponding random component of the model across all alternatives. In Arena, one can add a stream number after parameter-value arguments to realize the synchronization (e.g. Exponential

(12,2) for one system and Exponential (6,2) for the other with number 2 being the stream number). It is also advised to generate the randomness at the beginning of the model (i.e., when creating new entities) as much as possible. Doing so avoids mismatched random number streams at the latter part of the model where one system differs with the other. For example, the same entity (child) may receive mental health treatment in one system yet unable to do so in another system with less capacity. As a result, from that point on, the child likely uses different stream of random numbers in the two systems.

Despite the potential advantages, great care must be given when applying CRN. There is no proof that CRN will always work. [46] A pilot study may provide valuable feedback on the efficacy of CRN in reducing the variance of the difference. For more details about CRN and synchronization and its realization in Arena, see Law [46] (section 11.2) and Kelton [6] (section 12.4).

3.4 Specific Aim Two

3.4.1 Problem formulation.

Aim two is to assess how the accuracy of the screening tool affects the life course of young offenders. We examine this issue in a more simplified context. Specifically, we assess subsequent crimes at different levels of screening sensitivity and specificity, fixing other factors such as the prevalence of the disorder within juvenile justice system, positive effect of the treatment, and the adverse effect of being incarcerated for those false negatives.

Figure 3 illustrates the conceptual framework for aim two. The model also starts with youth age 10-17 and gets arrested first time for a crime. Every child has a dichotomous true underlying disorder status. At intake, the youth goes through a screening process that may identify him as disordered or not. Based on screened status, a judge may sentence him to receive treatment (for those screened as disordered) or to detention (for those screened as normal). For those truly normal youth who go to detention, they serve as the reference cases. As compared to them, those truly disordered youth who receive the treatment have a longer time to next offense (reduced recidivism); those truly disordered youth who go to detention have a shorter time to next offense (increased recidivism); those truly normal youths who receive treatment have added costs of the treatment yet no effect. Again, those who are 18 or older exit the system with their treatment and arrest history recorded.

Key Model Assumptions for Aim Two

- Juvenile is defined as children age 10 to 17
- The initial and ending condition of the model does not matter (steady-state)
- The first-time offending follows an exponential distribution
- The true risk status is dichotomous
- The screened risk status is dichotomous
- When a youth is released or gets arrested again, his age is checked and if he is older than 18, he exits the system
- Each time the youth is arrested, his number of total arrests is updated only when he is less than 18.
- The mental health screening tool has specificity and sensitivity
- The judges make decision solely based on the risk status of the offenders at screening
- The capacity of the mental health facility is unlimited
- The capacity of detention facility is unlimited
- The recidivism depends on the child's true risk status
- The time to next offense follows an exponential distribution
- Community treatment is at least as effective as the residential placement, or even better

3.4.2 Model parameters and output measures.

Table 8 provides a list of key model input and output measures for Aim Two.

3.4.3 Model assumptions.

Key model assumptions for Aim Two are summarized in the text box above.

3.5 Summary

The above outlines the key steps in a sound simulation formulated by Law. [46] As we emphasize before, this process is an iterative one and we go back to previous steps when necessary.

Figure 3. Conceptual Framework for Aim Two

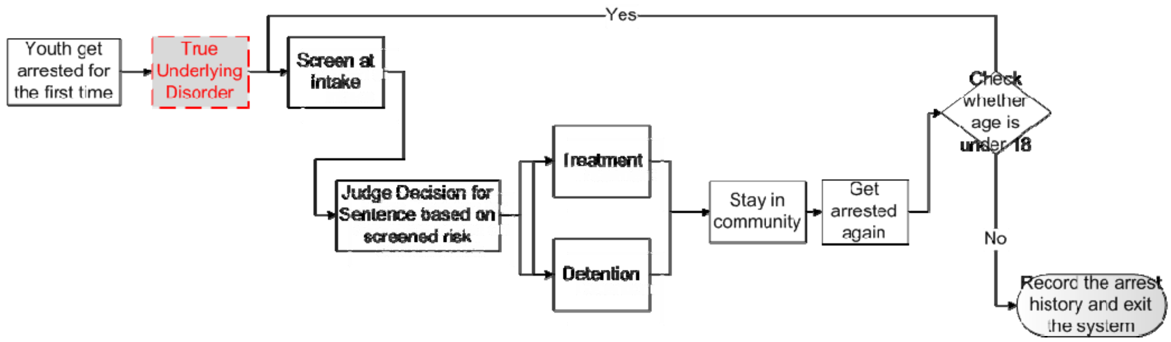


Table 8. Key Model Parameters for Aim Two.

Input Measures	**Values**
Rate of first-time offending	EXPO(1) days
Prevalence of disorder among first-time offenders	70%
Sensitivity	100%
Specificity	100%
Time spent in detention	EXPO(183) days
Time spent in treatment	TRIA(30,120,180) days
Average stay in community until next offense for incarcerated youth	EXPO(270) days
Effect of treatment on false positives	None
Effect of treatment on true positives	double the average stay in community for incarcerated youth
Effect of detention on false negatives	half the average stay in community for incarcerated youth
Output Measure	
Total number of youth entering adulthood with multiple offenses	

CHAPTER 4 RESULTS

4.1 Model Verification and Validation

Because the current model is highly conceptualized and the juvenile justice systems across the U.S. are highly diversified, also because we do not have individual-level data, we carried out the verification and validation of the model as far as possible in the standard way. For verification, we have performed many of internal consistency checks to ensure the model was logically correct and producing reasonable results, especially under extreme values. For validation, we did several things. First, we consulted with the juvenile justice experts in Washington State, the data source for the majority of our model parameter estimates. They confirmed that the conceptual model is a reasonable representation of the juvenile justice system in general, the three risk categories for re-offending are sensible, and the factors that we consider when assigning the youth to those risk categories are sensible. They are willing to provide individual-level data to refine some of the parameter estimates in the near future. In addition, we consulted MST experts about the mental health component of the model and got positive feedback.

Meanwhile, we also check other data source for consistency. For example, we examined the dispositions in the Philadelphia birth cohort [64] and found that 10% of the offenders were institutionalized, 14% received community disposition, and the rest 76% were either released without arrest, or arrested but not adjudicated. These figures are very close to what we have (see Table 4) for detention (9%), community supervision (15%), and diversion (76%). This indicates that even though we obtain majority of the estimates using Washington

State data, those figures are comparable with juvenile justice system in other places such as Philadelphia.

4.2 Specific Aim One

4.2.1 Warm-up length and number of replications

We examine several measures to decide the warm-up length beyond which the system has been stabilized. These include several outcomes of interest: the percentage of chronic offenders among all the juveniles exiting the system; the percentage of high-risk offenders exiting the system; and the percentage of unmet mental health needs. In addition, we examine one commonly used system performance measure: total work in process (WIP). In our context, this measure represents the total number of children currently being processed in the juvenile justice system. Stabilizing this measure enables us to distinguish the effects of population growth from features of the system that will occur whether there is growth or not. Policy makers may be interested in either effect, or both. Therefore, we decide to use all four measures to choose a common warm-up period.

We do so by letting the model run for 50,000 days in 5 replications and plot those measures over time in Figure 4 through Figure 7. From the plots, one can see that after the system runs for about 10,000 days, all five measures appear to be stabilized. Therefore, we choose 10,000 days as the warm-up length.

Next we need to decide the number of replications necessary to achieve the desired precision for the results. There is always a trade-off between the computational speed, the run time, and the desired precision. In our case, we have a warm-up length of 10,000 days. If we run an additional 100,000 days as in standard practice, it took more than half an hour for one replication. It is unrealistic given we have so many scenarios and replications. So we adopt the following approach.

Figure 4. Deciding Warm-up Length Based on Percentage of Multi-Offenders

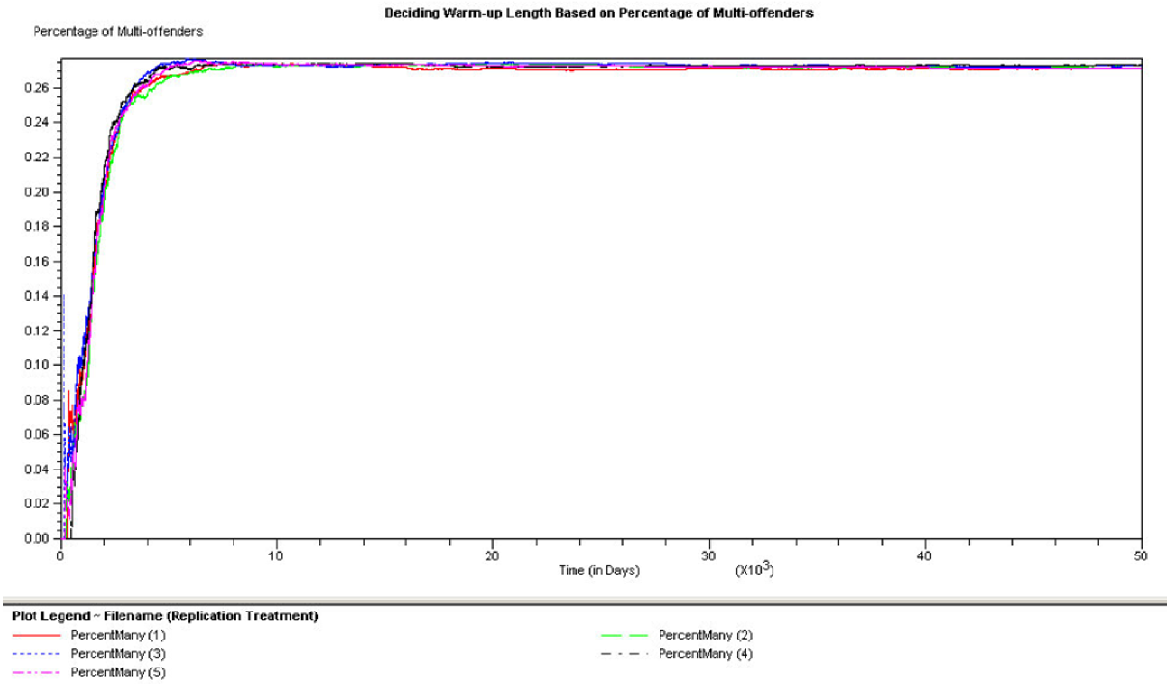


Figure 5. Deciding Warm-up Length Based on Percentage of High-risk Offenders

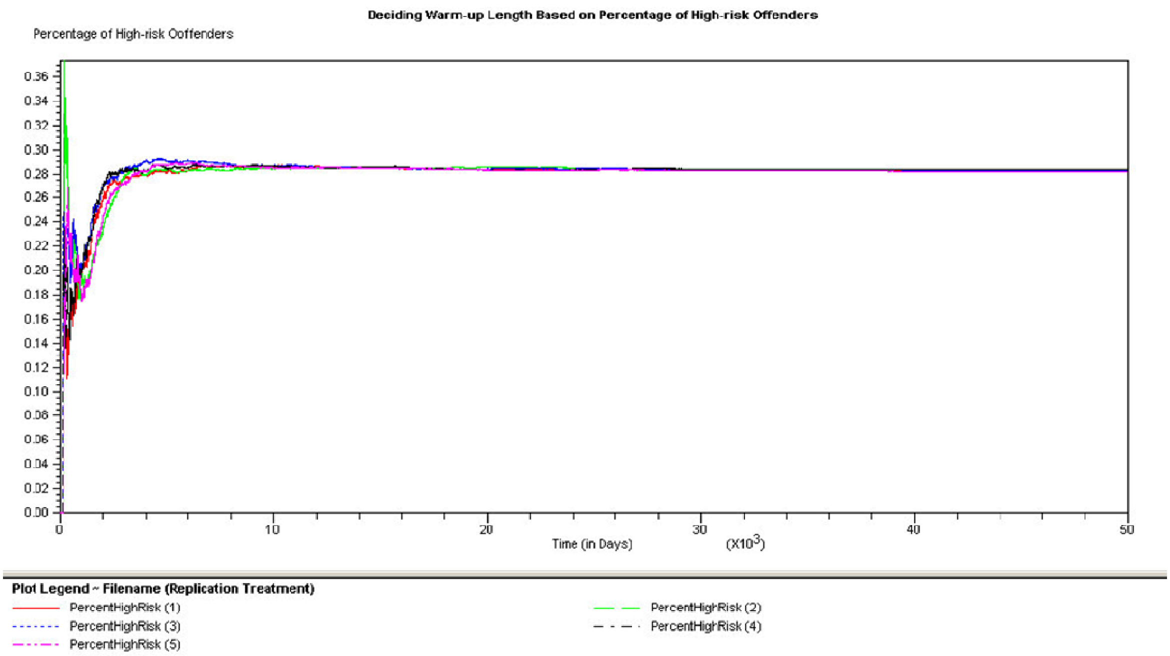


Figure 6. Deciding Warm-up Length Based on Percentage of Youth with Unmet Needs

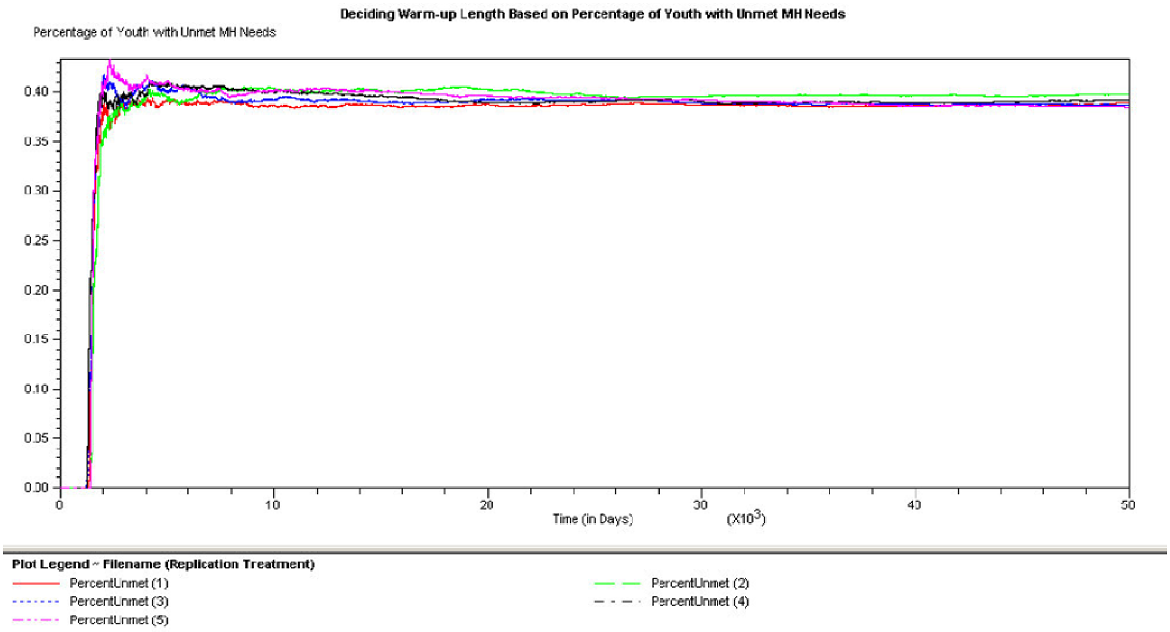
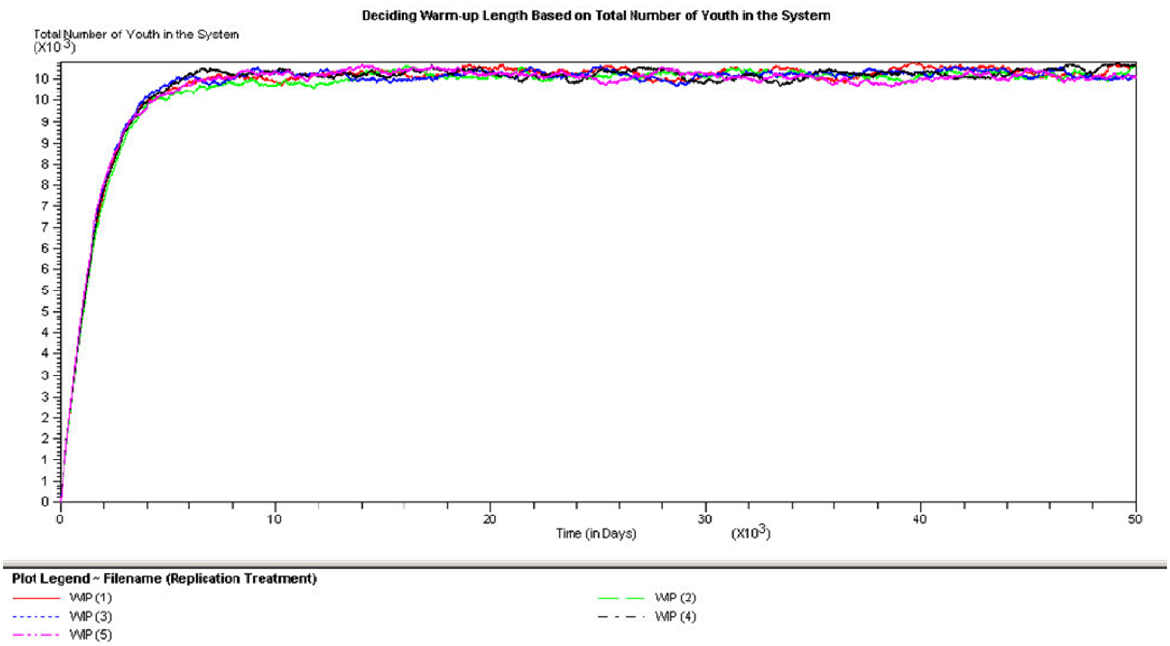


Figure 7. Deciding Warm-up Length Based on Total Number of Youth in the System



First, we run a single replication in a very long run (50,000 days with first 10,000 days as warm-up) and obtain the batch mean computed automatically by Arena for all the tally and time-persistent statistical output. The half-width is within 0.3% of the mean. Then we shorten the total run length to be 30,000 days. Now the half-width is within 0.6% of the mean. And we further shorten the total run length to be 20,000 days. The half-width is around 0.8% of the mean. Such a precision is good enough for our purpose of comparing systems. Therefore, we set the total run length to be 20,000 days.

If we run a single scenario, we can just run the model once and obtain the results. But we have designed the experiment and need to examine different levels of the factors we choose. And we have to do this in a systematic way in Process Analyzer. However, PAN does not support batch means method. So we set up the run length to be 20,000 days and run 10 replications. The resulting half-width is within 0.7% of the mean. When we reduce the number of replications to 5, the resulting half-width more than doubled. Therefore, we eventually decided to run a total length of 20,000 days for 10 replications for each scenario.

4.2.2 Baseline scenario.

We define the baseline as everyone who is sentenced to detention goes to detention. No treatment option is offered to those youth. Therefore, no mental health service utilization data are provided.

After running for approximately 27 years, on average, a total of 49974 youth enter juvenile justice system and become adults at some point and exit the system. Among them, 27.4% youth are classified as high-risk for re-offending based on his last screened risk status. 31% of them enter adulthood with more than two offenses (multi-offenders). Among those multi-offenders, 71% of them are high-risk. The average cost is 3360 (in 2000 dollars) for all the offenders that have a contact with the juvenile justice system, or 6723 (in 2000 dollars) for either multi-offenders or high-risk youth. The average number of arrests among those multi-offenders is 2.9.

Table 9. Simulation Results for Baseline Scenario.

Output Measures	Average across Replications
Total number of youth exit the system upon turning 18	49974
Average cost	$3360 (in 2000 dollars)
% of high-risk for reoffending based on last screened status	27.40%
% of youth enter adulthood with multiple offenses	31%
Among those with multiple offense:	
% of high-risk	71%
Average cost	$6723 (in 2000 dollars)
Average arrest	2.9

4.2.3 Mental health service utilization.

4.2.3.1 Treatment Capacity.

Figure 8-12 depicts the relationship between treatment capacity and mental health service utilization at different levels of treatment effectiveness when we divert 100% the high-risk youth from detention to treatment. We can see based on current caseload, if we increase the number of slots from 100 to 200, the total number of youth being treated gradually increase and then level up after 180 slots (Figure 8). Meanwhile, the percentage of youth being untreated also decreases to 0 beyond 180 slots. We observe similar pattern for total treatment sessions, service utilization, and total number of high-risk youth being treated.

When we compare the above figures at different levels of treatment effectiveness, we see that at the same level of capacity, highly effective treatment (80% reduction in recidivism) treats more problem youth, have less treatment sessions, lower percentage of untreated, and lower service utilization as compared to a moderately effective treatment (40% reduction in recidivism). This is because a youth treated with highly effective treatment stays in the community longer, which results in more youth aging out of current system before their next attempt to commit a crime.

Figure 8. Total Number of Youth Treated

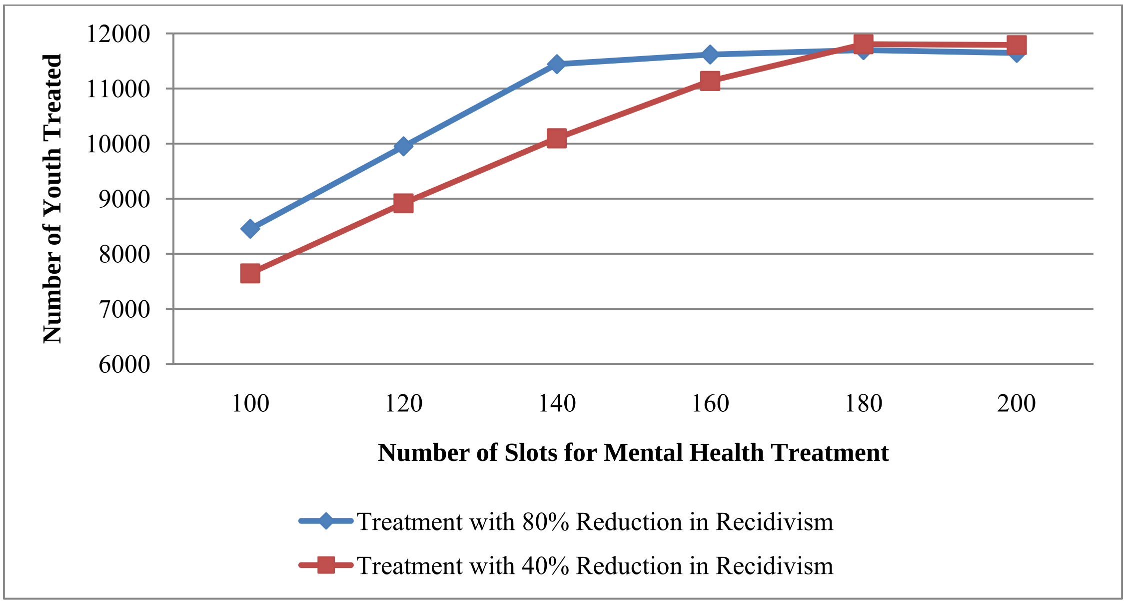


Figure 9. Total Number of High-Risk Youth Treated

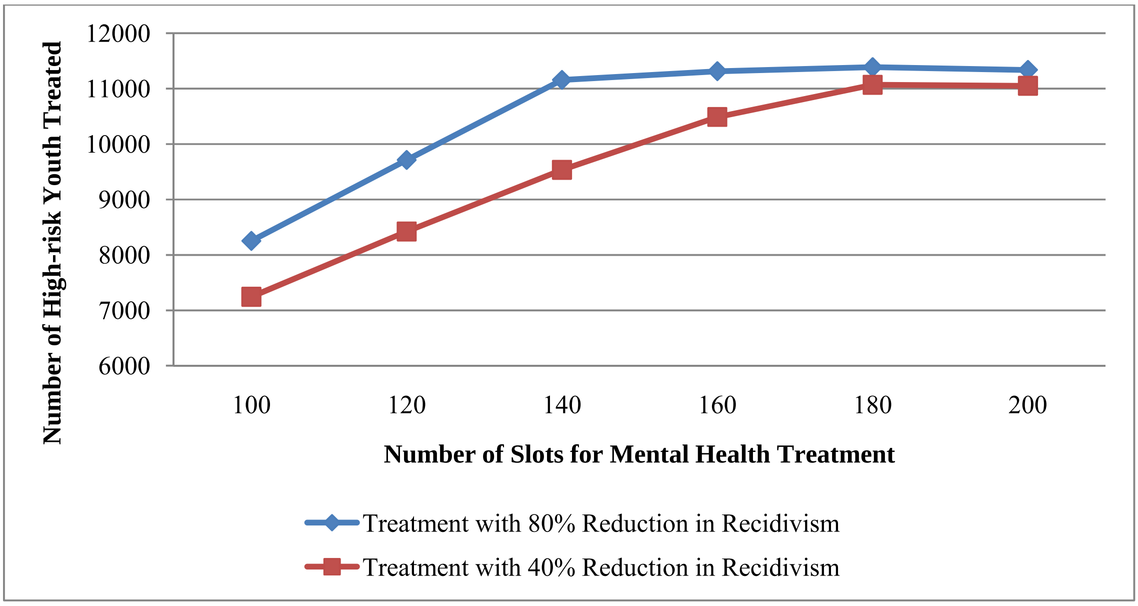


Figure 10. Total Treatment Sessions

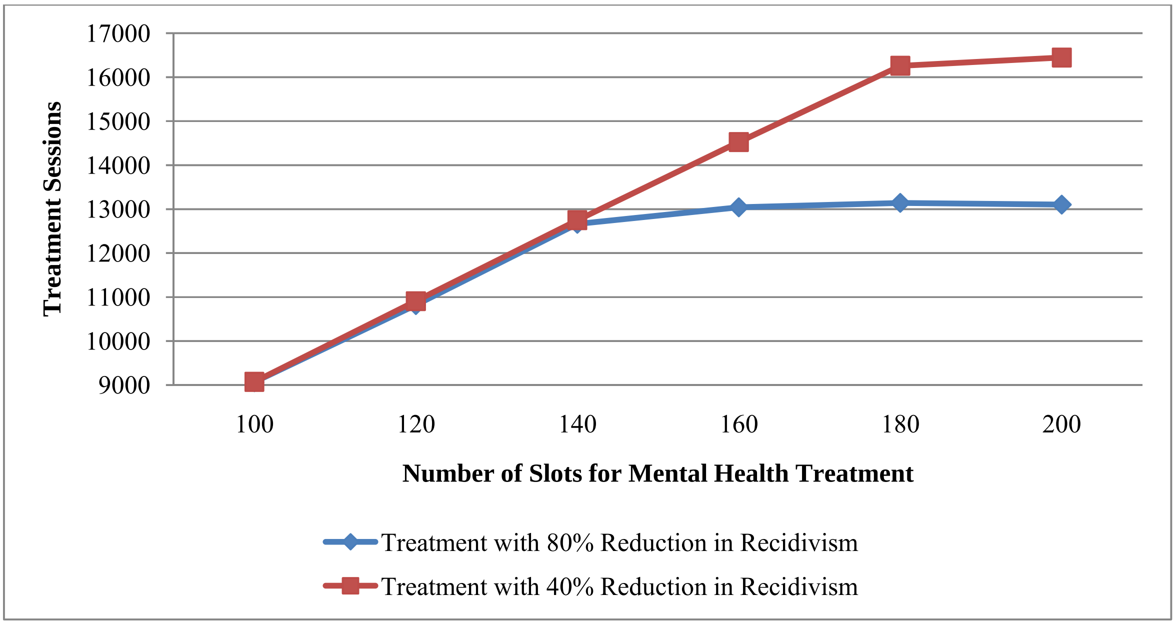


Figure 11. Percentage of Untreated Youth

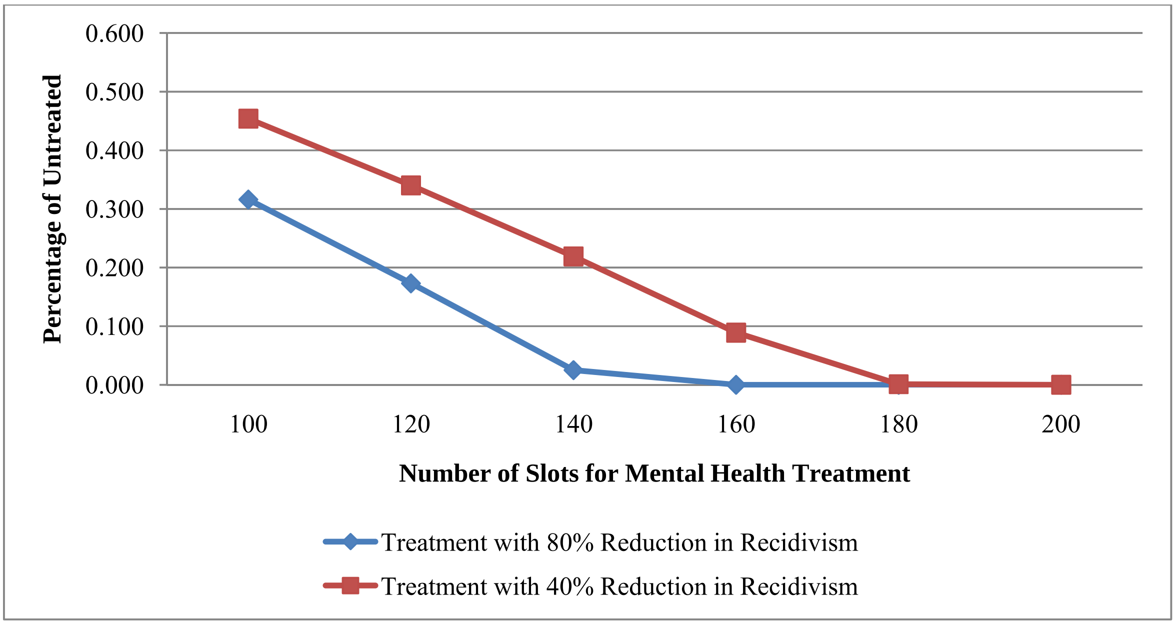
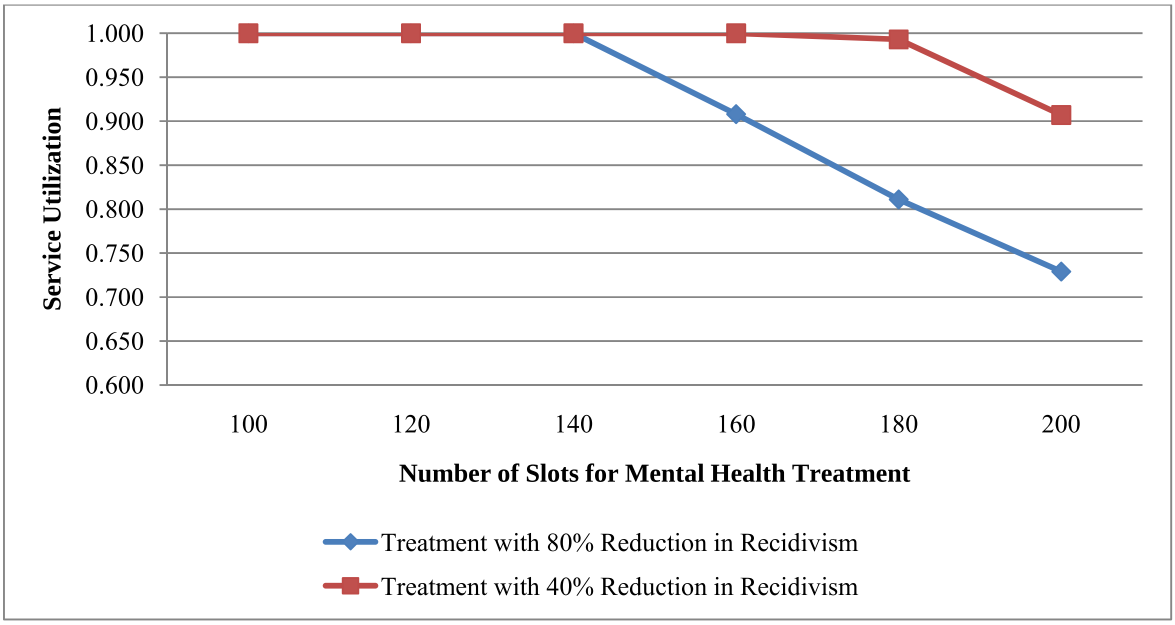


Figure 12. Treatment Utilization



What is the relationship between the needs for mental health service and treatment capacity? Let us do some calculation. There are around 50,000 youths exiting the system within 10,000 days based on the simulation results. This indicates that every year there are about 1,800 youth passing through juvenile justice systems and age out. We can also obtain this number from the exponential distribution we use to generate those entities. Among them, about 27% of youth (approximately n=486) are classified as high-risk based on the simulation result. A treatment capacity of 100 slots can serve 5.5% of all the youth and 21% of the high-risk youth. Similarly, a treatment capacity of 180 slots can serve 10% of all the youth and 37% of the high-risk.

4.2.3.2 Proportion diverted from detention to treatment.

Figure 13-16 depicts the relationship between percentage of youth diverted to treatment from detention and mental health service utilization at different levels of treatment effectiveness when the capacity is 100 slots. We can see based on current caseload, if we decrease the percentage of youth sentenced to treatment, the total number of youth being treated remain unchanged between 100% and 60% and gradually decrease (Figure 13). Meanwhile, the percentage of youth being untreated also decreases to 0 if we divert less than half of the youth to receive treatment. We observe similar pattern for total treatment sessions, service utilization, and total number of high-risk youth being treated.

Figure 13. Total Number of Youth Treated

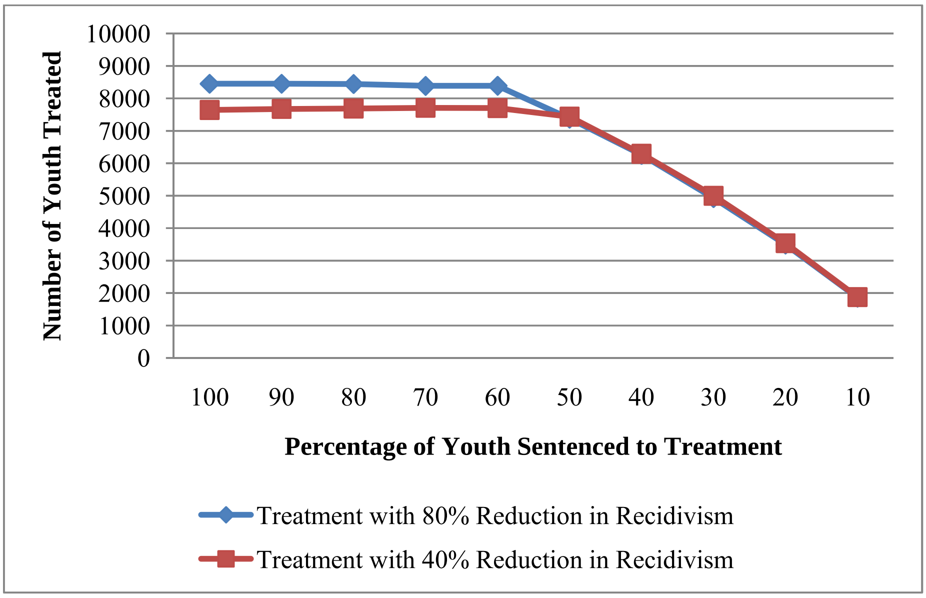


Figure 14. Total Treatment Sessions

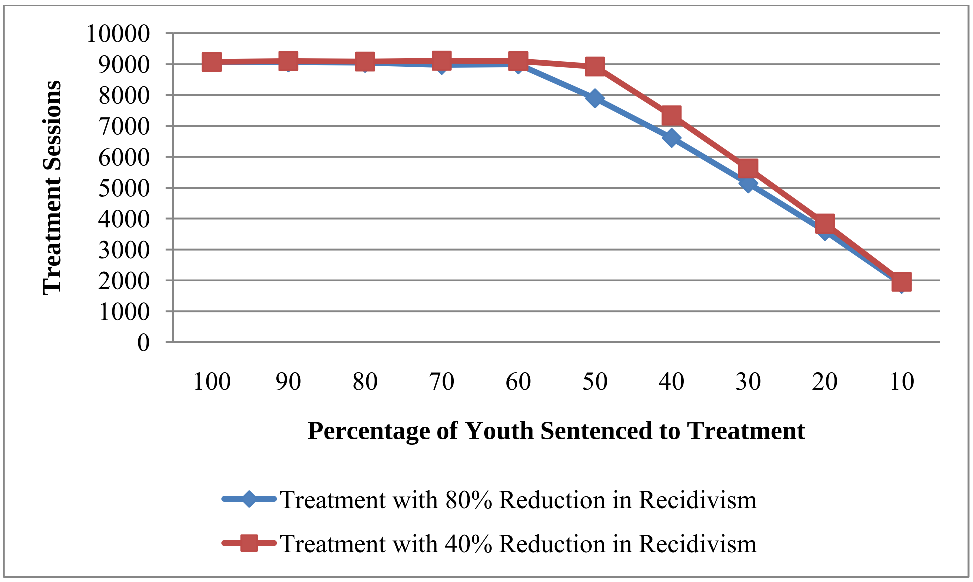


Figure 15. Percentage of Untreated Youth

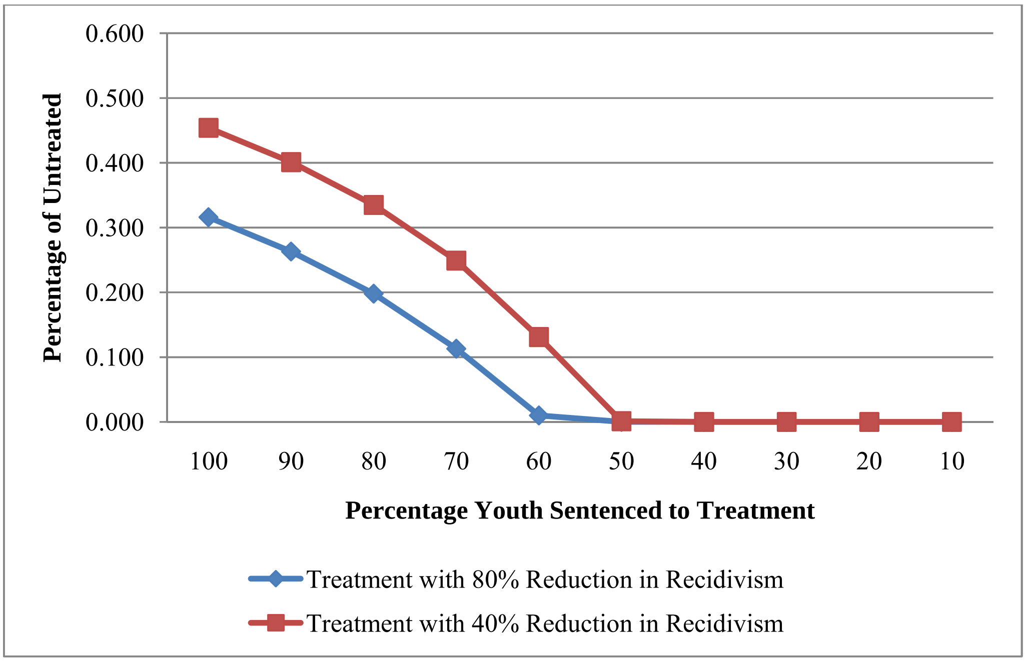
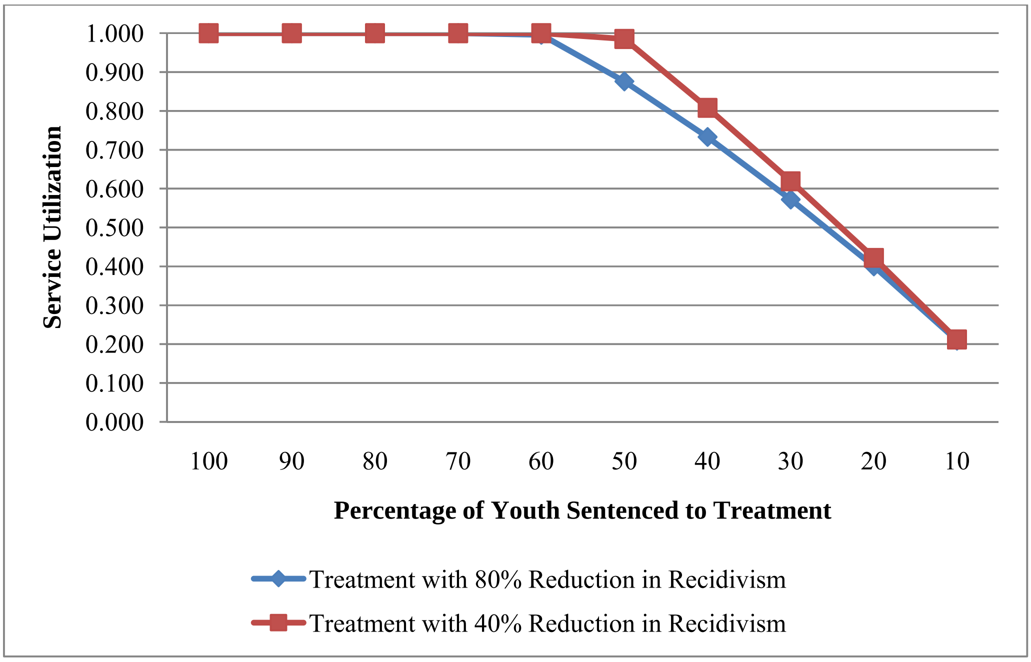


Figure 16. Treatment Utilization



Again when we compare different treatments, we see that at the same level of diverting youth to treatment, highly effective treatment treats more problem youth, have less treatment sessions, lower percentage of untreated, and lower service utilization as compared to a moderately effective treatment.

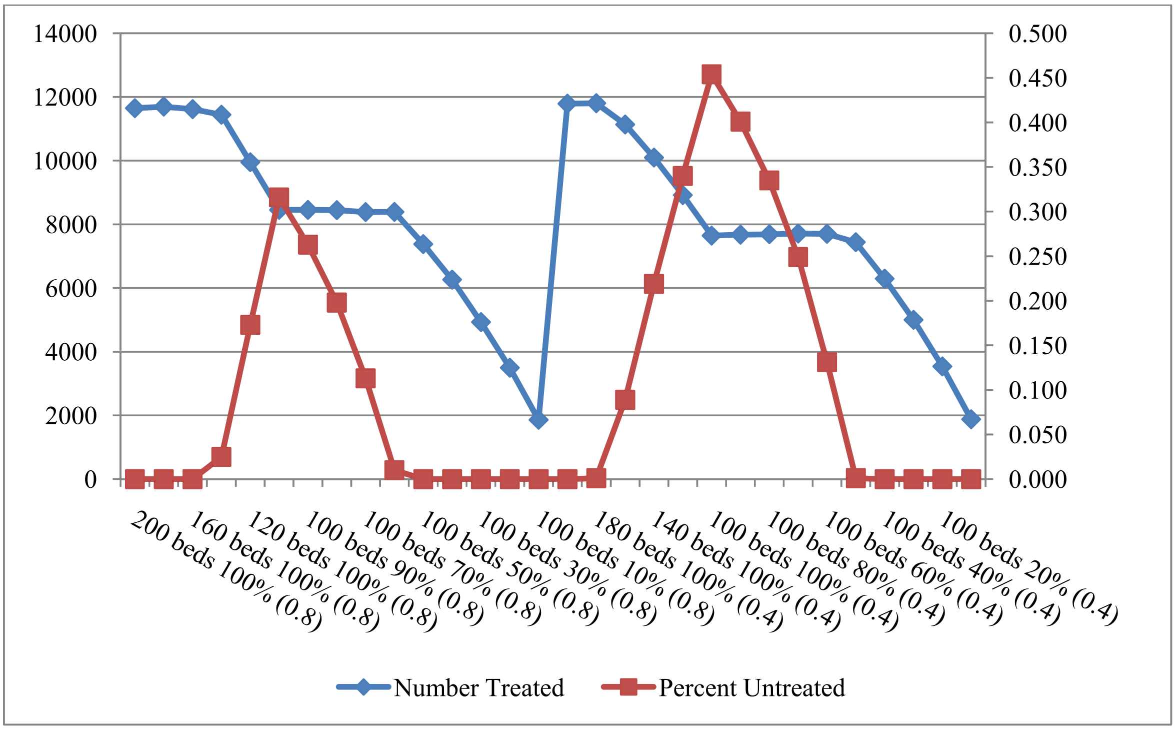
For a high-risk youth (approximate n=486, calculated from above), he has a 56% chance to be sentenced to detention based on the estimate we use in the model. If 100% of them are sentenced to treatment, the number of youth in need of mental health service is 272. On the other hand, if only 60% of them are sentenced to receive treatment, the number in need decreases to 163. A capacity of 100 slots will satisfy 37% of people in need in the first case (the same result as above) and 61% in need in the second case.

4.2.3.3 Link between factors.

There is certainly an intrinsic link between treatment capacity, the proportion treated, and the effectiveness of the treatment. Although an analytical solution to quantify the link is unlikely given the complicated relationship within the system, Figure 6 depicts the relationship in a limited way based on the simulations we choose to run. If one runs all the possible combination of the three factors, one gets a surface with 3 axes representing the three factors. For a particular outcome (e.g., total number of youth treated), one will get three points on that surface of the same height.

Figure 17 also depicts the relationship between total number of youth treated and the proportion of youth not being treated. The graph shows several interesting things. First, the ideal situation is to maximize the former while minimizing the latter. This is achievable only by consuming more resources. However, consuming more resources does not necessarily achieve the desired outcome. There are certain points beyond which even though more resources may be available, the effects on the outcome have reached the maximum limit as decided by the dynamics of the system. Such points in current system set up are 180 slots with 100% treatment rate or 100 slots with 60% treatment rate. Furthermore, under constrained resources, optimization may not be achievable, and policy makers have to weigh the trade-off between resource consumption and the outcome they desire. For example, one can fix their resource capacity and find the best scenario at alternative levels of the other factors. There are also certain scenarios that consume more resource yet achieve little effect (e.g. 120 slots 100% treatment rate for highly effective treatment or 100 slots 100% treatment rate for less moderately effective treatment). Policy makers should try to avoid those situations.

Figure 17. Total Number Treated and Percent Untreated



4.2.4 Criminal outcomes.

Figure 18-24 provides a series of graphs depicting the relationship of various criminal outcomes and the three factors we consider: capacity, proportion treated, and treatment effectiveness.

Figure 18-21 present the offender profile of youth entering adulthood by treatment capacity, proportion treated, and effectiveness of the treatment. In order to provide a comprehensive view of the system, we plot the mean number of youth with multiple offenses and their 95% confidence interval across all the scenarios we considered. Figure 22 depicts this relationship. One can see that the majority of the scenarios have significantly less number of multi-offenders than baseline. Generally speaking, the number is lower for a highly effective treatment, or scenarios with higher proportion of youth being diverted to treatment, but not much different for treatment with different capacities.

Figure 18. Number of Youth in Different Offender Category

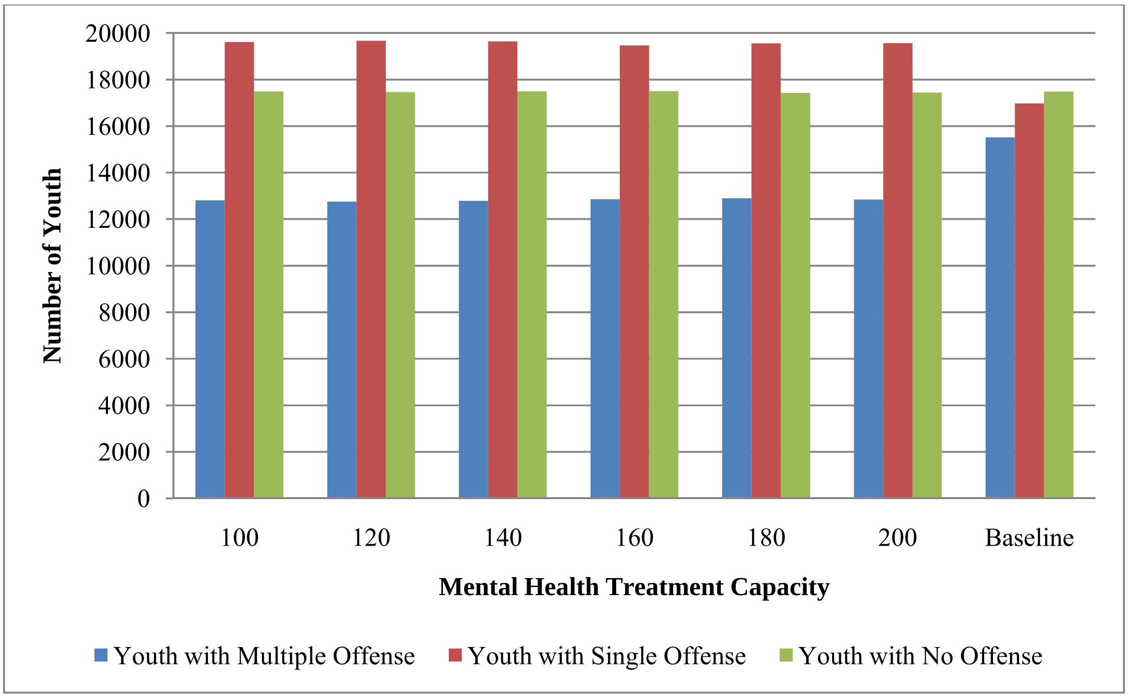


Figure 19. Number of Youth in Different Offender Category

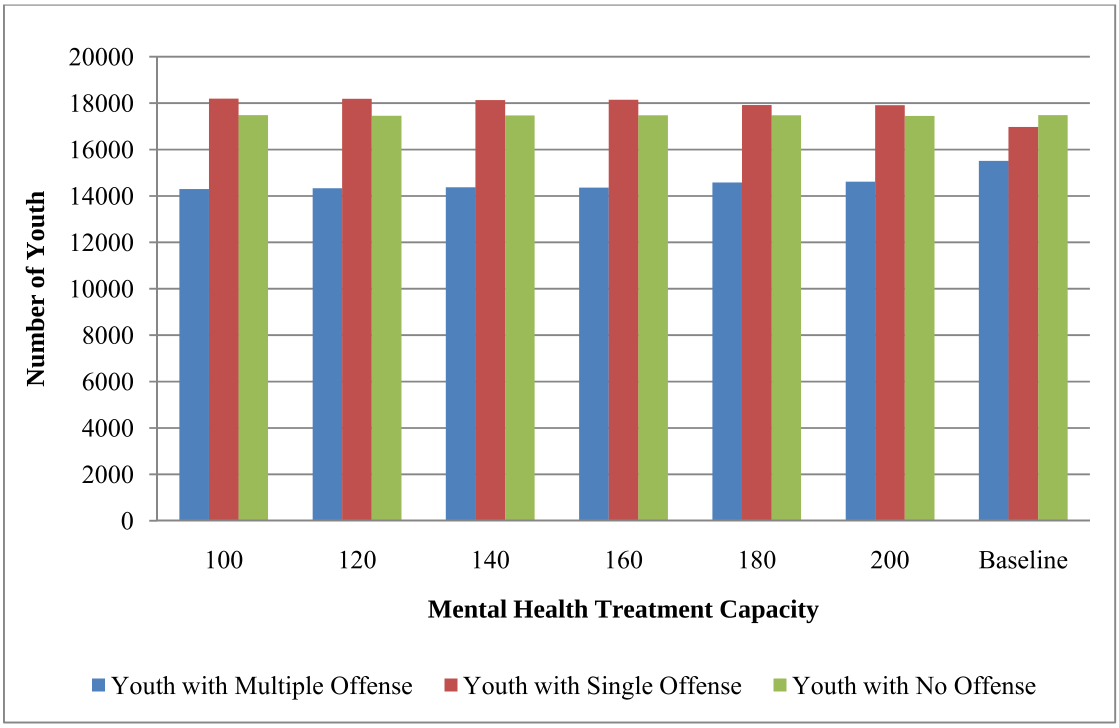


Figure 20. Number of Youth in Different Offender Category

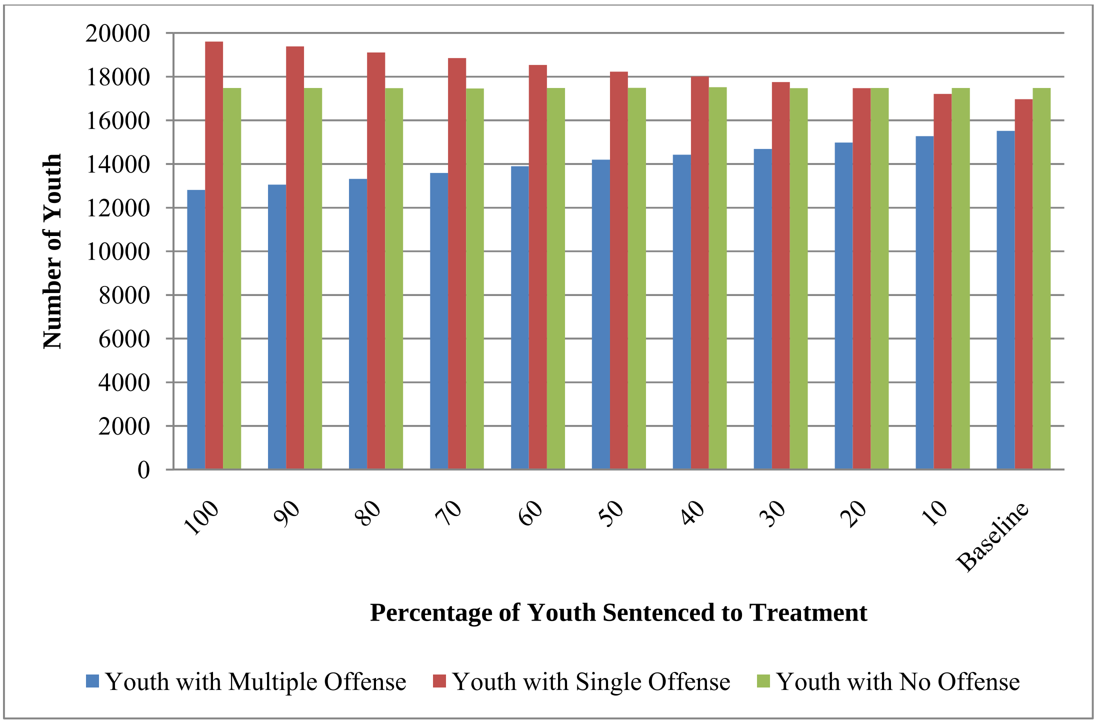


Figure 21. Number of Youth in Different Offender Category

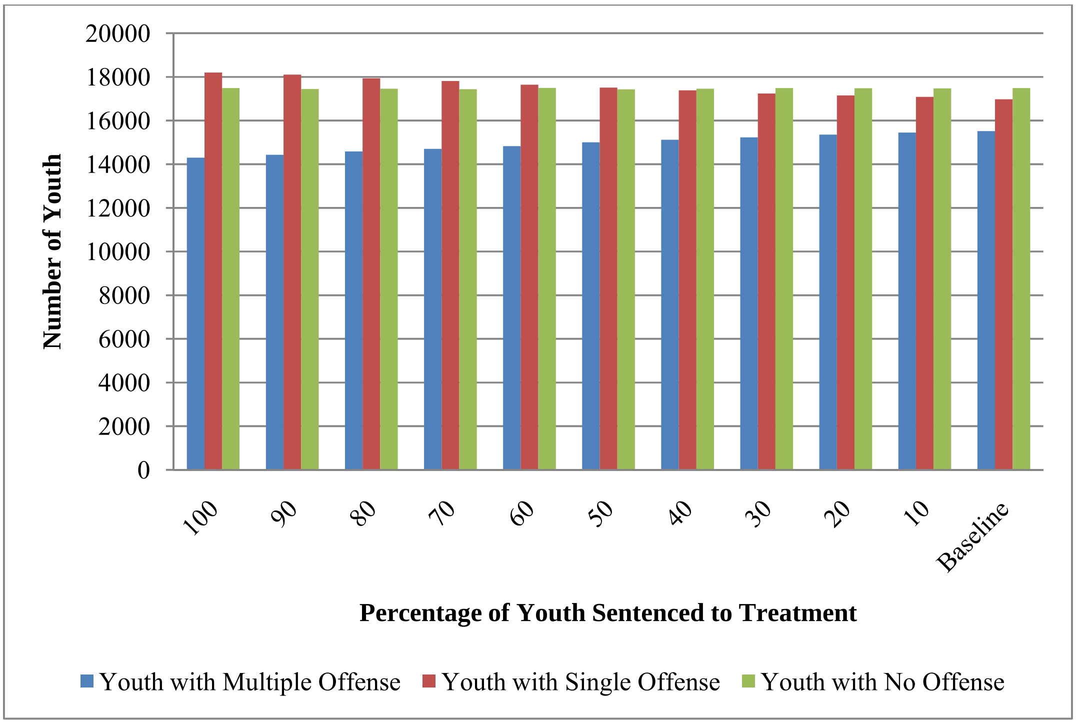
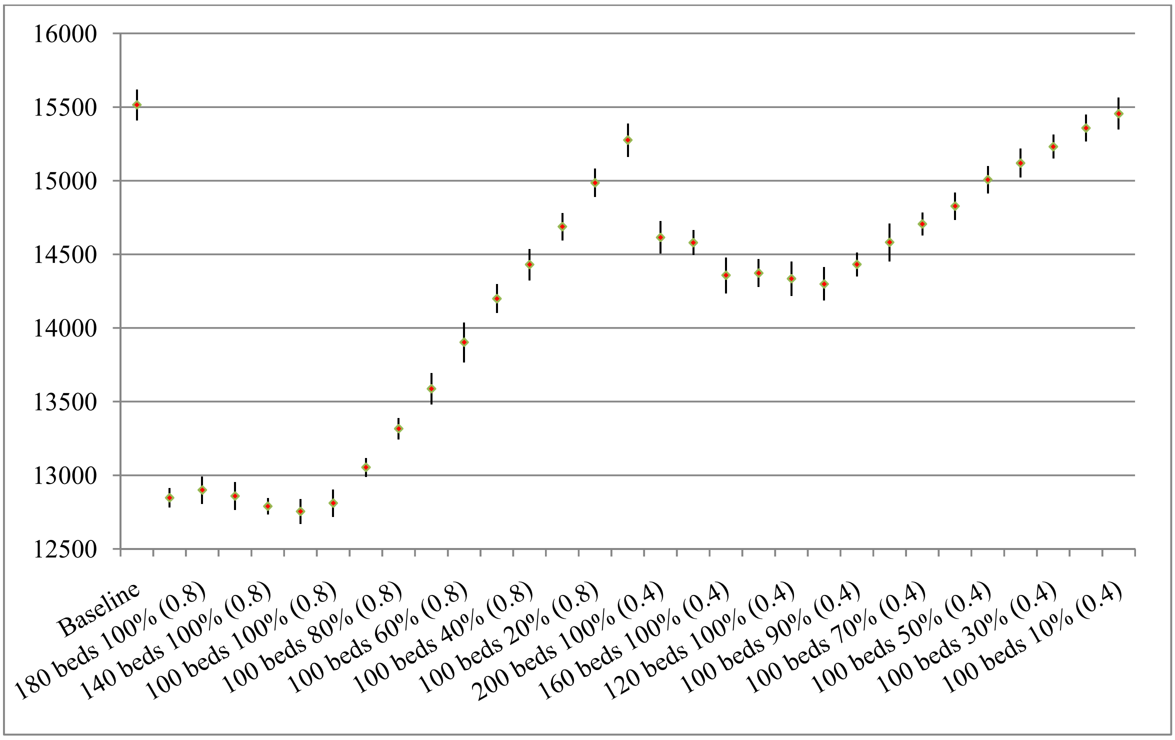
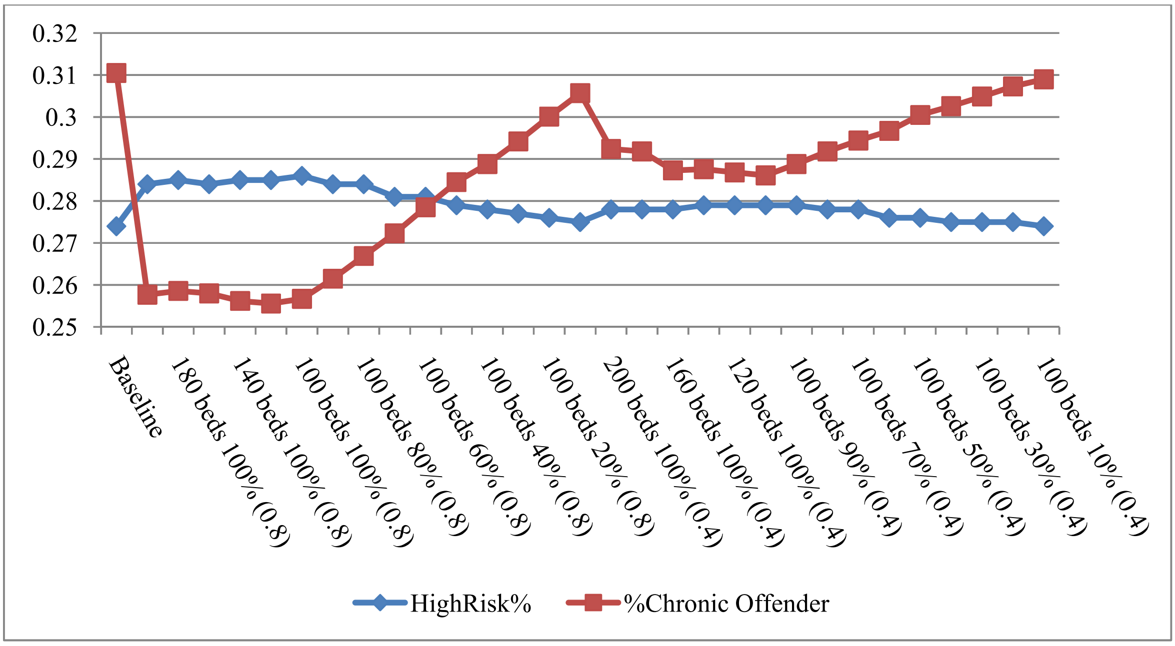


Figure 22. Number of Youth Entering Adulthood With Multiple Offenses with 95% Confidence Interval



The percentage of youth exiting the system with multiple offenses or were screened as high-risk are plotted in Figure 23. It shows similar relationship between multi-offenders and the three factors as we discussed above. As to the percentage of high-risk offenders, it shows an interesting pattern quite contrary to one's expectation. The percentage is higher for more effective treatment with bigger capacity. A possible explanation is that the risk status was based on the last screening before the youth exits the system. With a highly effective treatment or one that has more capacity, more high-risk youth tend to receive treatment and subsequently stay longer in the community. Those youths are more likely to age out of the system before they commit another crime. Whereas for a treatment that is less effective or with fewer slots, the youths subsequently stay shorter in the community. Based on current model set up, if a youth commits a non-violent felony on previous arrest, he has 37.5% chance to commit a misdemeanor as next offense; or if a youth commits a violent felony on

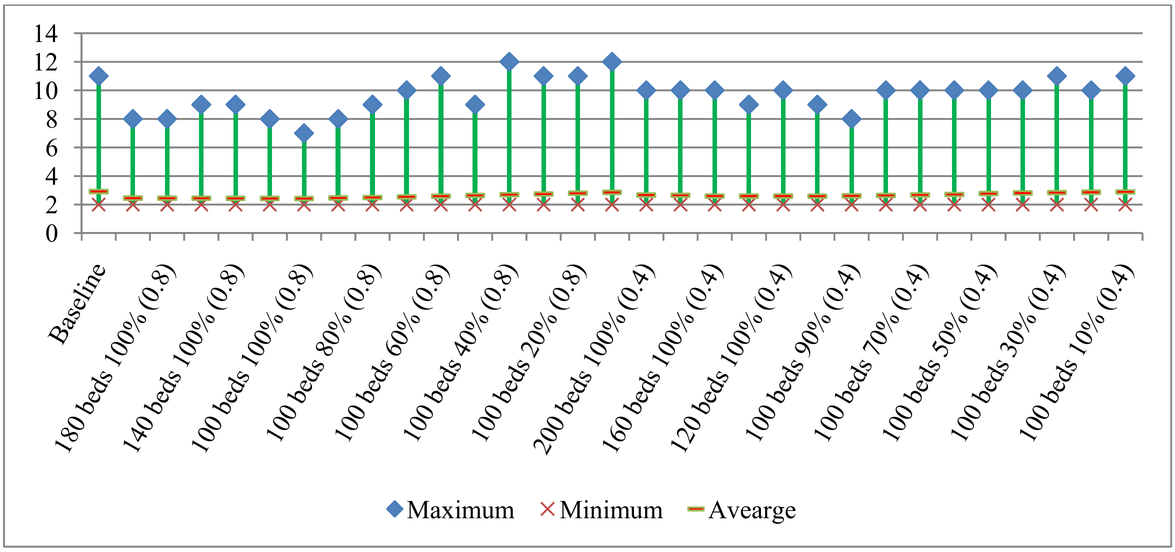
Figure 23. Offender Profile by Scenario



previous arrest, he has 43% chance to commit a misdemeanor as next offense. Therefore, a proportion of those high-risk youth re-enter the system with less serious offenses that result in degrading their risk status. But in any case, the difference between those scenarios is within one percentage point, indicating that this measure is stable and are not very sensitive to the model set up.

Figure 24 shows the minimum, average, and maximum number of arrests for youth with multiple offenses. The average number of arrest is between 2.4 and 3, while the maximum number of arrests ranges from 8 to 11 across scenarios.

Figure 24. Average Number of Arrests for Multi-Offenders



4.2.5 Cost-effectiveness analysis.

In this section, we conduct a cost-effectiveness analysis to illustrate how discrete-event simulation model can be applied in economic analysis. As we described in Method section, we need to calculate an incremental cost-effectiveness ratio (ICER) for the dollar amount spent on one unit of improved outcome. We choose the number of youth entering into adulthood with multiple offenses as the outcome. Such a measure has strong implications both for public health and for potential cost saving. As we mentioned before, research has consistently found that a small group of youth ("chronic offenders") accounts for a substantial portion of all offenses, and they tend to have early onset of problem behaviors that continue into adulthood with more serious criminal activities.[9-11] As a result, the potential benefits of early prevention and effective treatment of juvenile crime are enormous. Although the measure of multi-offender used in this study is not exactly the same as the definition of "chronic offender" in literature, such analysis can still provide insight about the latter. Table 8 presents the results.

First we examine two particular policy scenarios: 180 slots with 100% treatment rate, and 100 slots with 60% treatment rate. These two scenarios are interesting because they represent certain points beyond which additional resource does not yield additional return. In these two cases, increase the number of slots to be more than 180 for the first scenario or sentencing more youth to receive treatment for the second scenario will not satisfy additional needs of the juvenile offenders for mental health.

Figure 25 plots the estimate of ICER for the two scenarios on cost-effectiveness plane. Each point represents one replication of the simulation for that particular scenario. We can see both scenarios decrease the number of multi-offenders as well as decrease the total cost of the system. If we draw a line from (0,0) to a point on CEA plane, the elasticity is the estimated ICER. In our case, we can see the same line goes through the center of the points for both scenarios, indicating the two policies probably will yield the same incremental effect with the same incremental cost. Policy makers can make their own choice based on their budget and other factors they deem important.

Figure 25. Incremental Cost -Effectiveness of Alternative Policy Scenarios Relative to Baseline

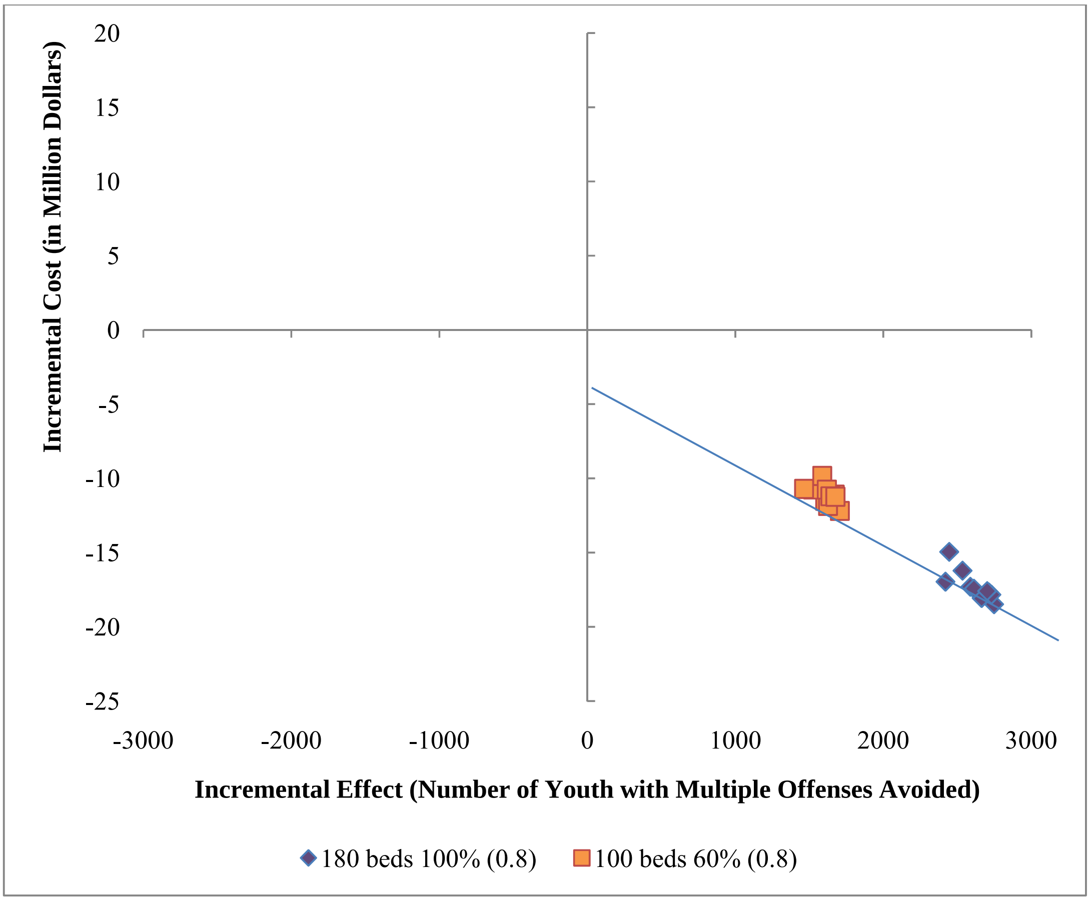
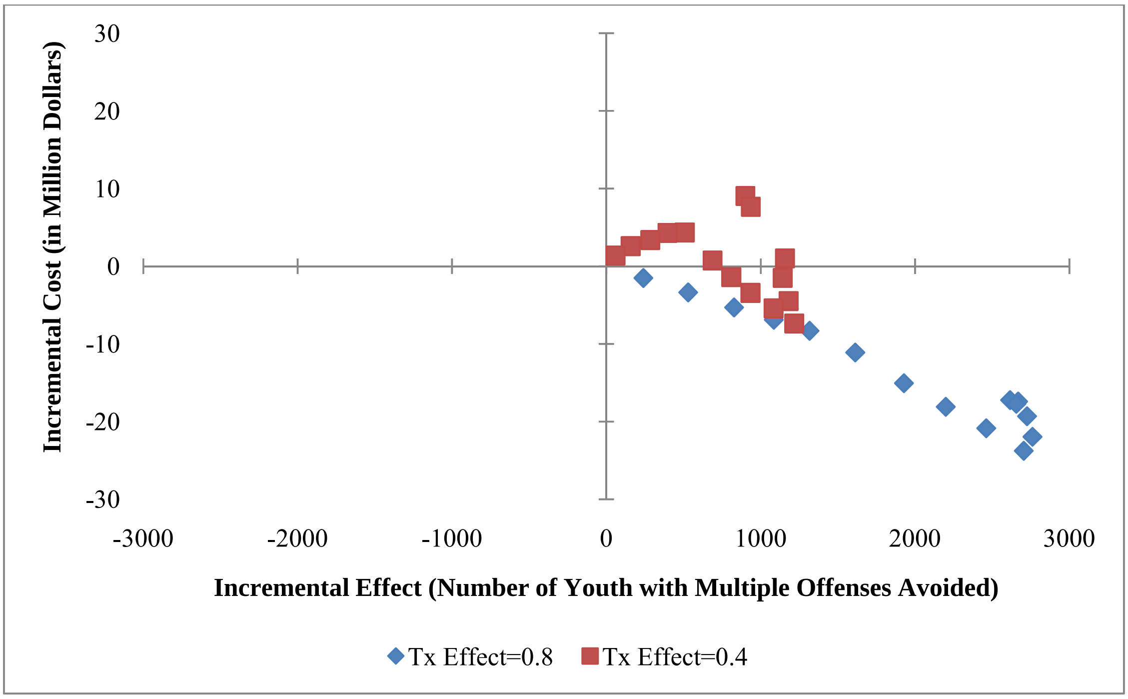


Figure 26 plot estimates of ICER for all the scenarios we have considered, separated by the effectiveness of the treatment. Generally speaking, all the ICER estimates for a highly effective treatment fall within the cost-saving part of the plane. The case is mixed for a less effective treatment. There are six scenarios with ICER falling on the cost-effective part of the plane. They represent 100 slots with 70% to 100% treatment rate, and 120 and 140 slots with 100% treatment rate. If we further increase the number of slots at the 100% treatment rate level (to be more than 140), or decrease the treatment rate at 100 slots level (to be less than 70%), we do not achieve cost-effective.

Figure 26. Incremental Cost-Effectiveness of Alternative



4.2.6 Sensitivity analysis.

We perform three sets of sensitivity analysis to examine whether our results are sensitive to alternative costing, discount rate, and formula for recidivism. For costing, we use another set of daily cost estimate also obtained from the Washington State juvenile justice system. Besides, we also test an annual discount rate of 3% (we use 5% originally). In addition, we examine an alternative formula for modeling recidivism for treatment. Those parameters are presented in Table 10.

Figure 27-29 depicts the selected criminal outcomes using alternative modeling of recidivism. We can see the relationship among factors still hold, but the estimates are higher with alternative recidivism. If we plug in an effect into the two sets of formula in Table 10, we can see the average stay until next offense for treated youth under alternative recidivism is only half of the original estimates. In another word, youth tend to stay much shorter in the community before committing another crime under alternative recidivism. They are more likely to commit more offenses and demand more mental health services before aging out of the system. That explains why all the numbers are higher for alternative recidivism. This is also part of the model validation, and we can see that the results change in the anticipated direction.

Table 10. Parameter Estimates for Sensitivity Analysis

Model Paramter	**Original**	**Alternative**
Cost Estimates	Total cost	Daily Average Cost (in 2000 dollars)
Diversion	1,138	1.7
Community Supervsision	2,234	5.97
Detention	6048 (annual)	105.38
Mental Health Treatment	4,743	4743 (per session)
Annual Discount Rate	5%	3%
Recidivism for Treated		
Low Risk	Expo(3.02*(-18*30.25/ln(1-(1-Effect)*0.867)))	Expo((1+effect)*821)
Moderate Risk	Expo(1.88*(-18*30.25/ln(1-(1-Effect)*0.867)))	Expo((1+effect)*435)
High Risk	Expo(-18*30.25/ln(1-(1-Effect)*0.867))	Expo((1+Effect)*270)

Figure 30 depicts the cost-effectiveness analysis under three sets of alternative models. We can see changing discount rate virtually has little effect on ICER. In addition, we see changing alternative costing do not change the effect side, but the cost greatly increases. Finally, when we change both costing and recidivism, the treatment options are still cost-effective, but in a smaller scale.

Those sensitivity analyses serve for two purposes. First, we can examine how sensitive our results are to alternative modeling of the key model parameters. Second, we can also validate the model by assessing whether the results change in the anticipated direction when we change the model parameters. We do not find anything abnormal with regard to the two purposes above.

Figure 27. Sensitivity Analysis: Number of Youth with Multiple Offenses

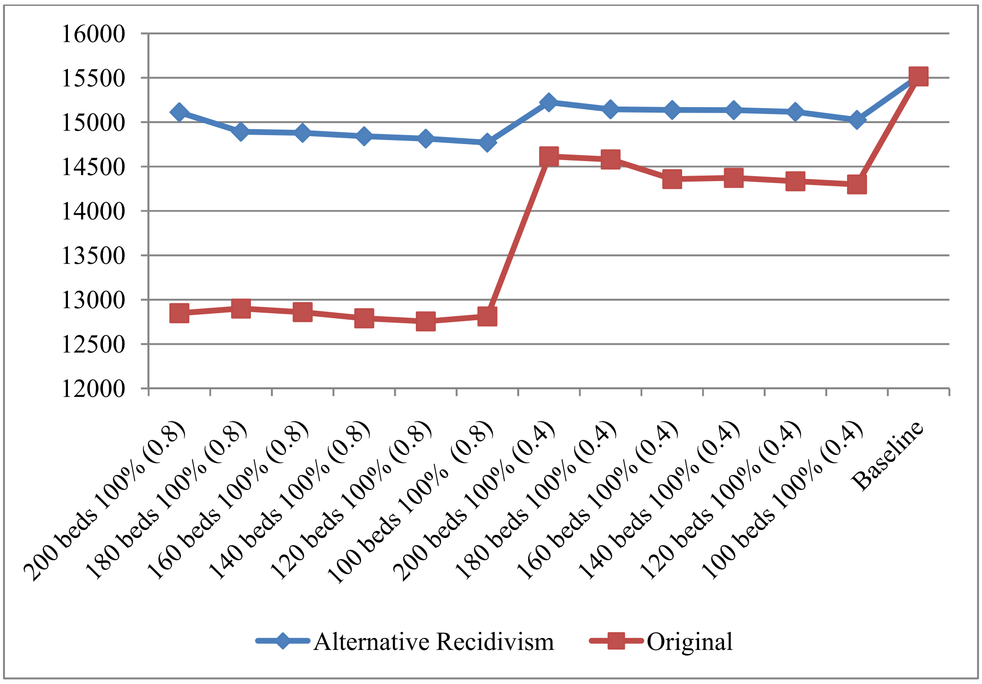


Figure 28. Sensitivity Analysis: Percentage of Youth with Multiple Offenses

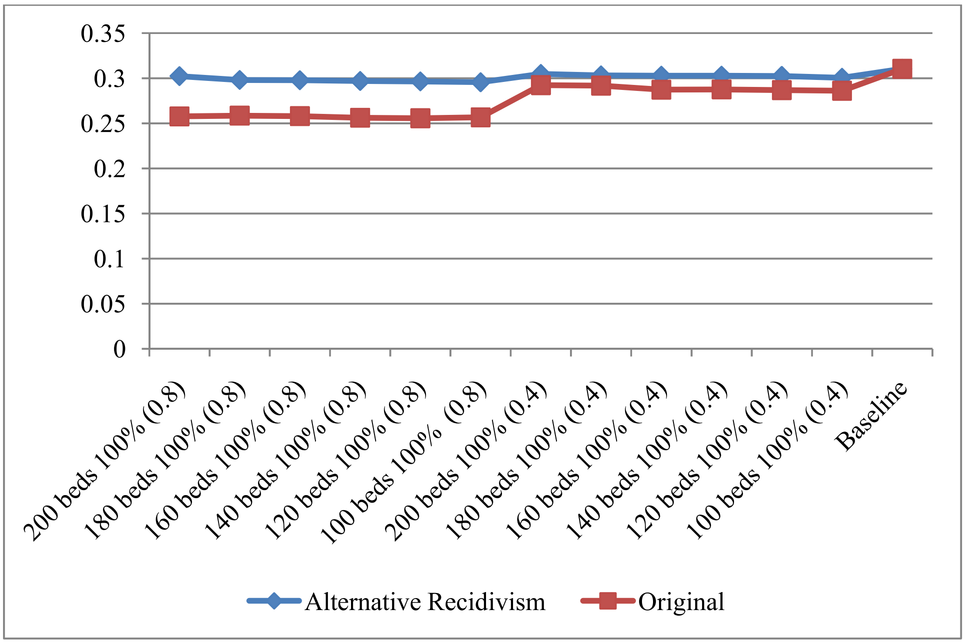


Figure 29. Sensitivity Analysis: Percentage of Untreated

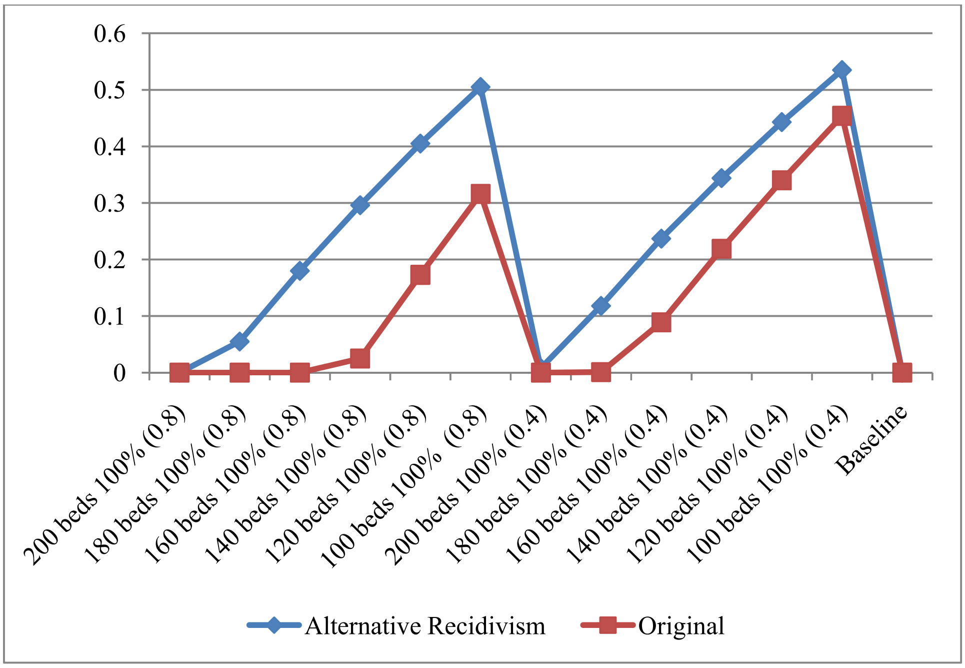
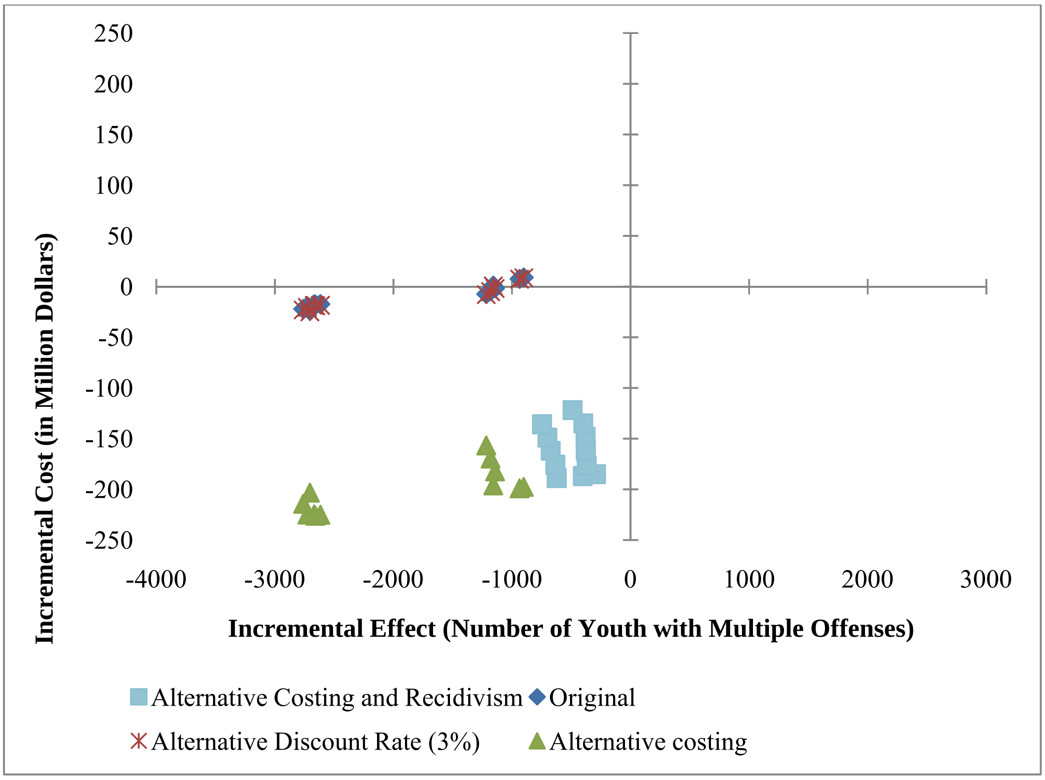


Figure 30. Sensitivity Analysis for Incremental Cost-Effectiveness



4.3 Specific Aim Two

As an extension to specific aim one, we examine the issue of screening sensitivity and specificity in aim two.

4.3.1 Warm-up and run length.

Similarly as how we decide the warm-up and run length, we choose 10000 days warm-up, 100,000 days total run length, and 5 replications to run the simulation.

4.3.2 Total number of youth exiting with multiple offenses.

We examine this measure at different levels of sensitivity and specificity. Other factors such as the prevalence of the disorder among detained youth, the effect of treatment on recidivism, the effect of false positive and false negative are fixed at pre-specified level.

Based on Figure 31 and 32, we see that the number of multi-offenders increase when the sensitivity or specificity gets worse. Counterintuitively, when we have perfect sensitivity, the number of multi-offenders is higher for a detained juvenile population with 30% disorder than the one with 70% disorder, whereas people expect a population with more troubled youth will surely create more multi-offenders. A possible explanation is that with a low prevalence and a perfect sensitivity to detect all the disordered cases, the percentage of youth being identified as disordered and receiving the treatment thus being exposed to “good effect” is lower. Since treatment has no effect on those false positives (normal youths who are screened as disordered), less youth are being “corrected” in terms of their stay in community until next offense. As a result, these youths are more likely to get involved in the juvenile justice system again and exit the system with multiple offenses.

We further hypothesize that the gap between the two lines depends on the treatment effect. For a juvenile population with high prevalence of disorder, a highly effective treatment will result in less youth exiting the system with multiple offenses. As a sensitivity

Figure 31. Number of Youth with Multiple Offenses by Specificity

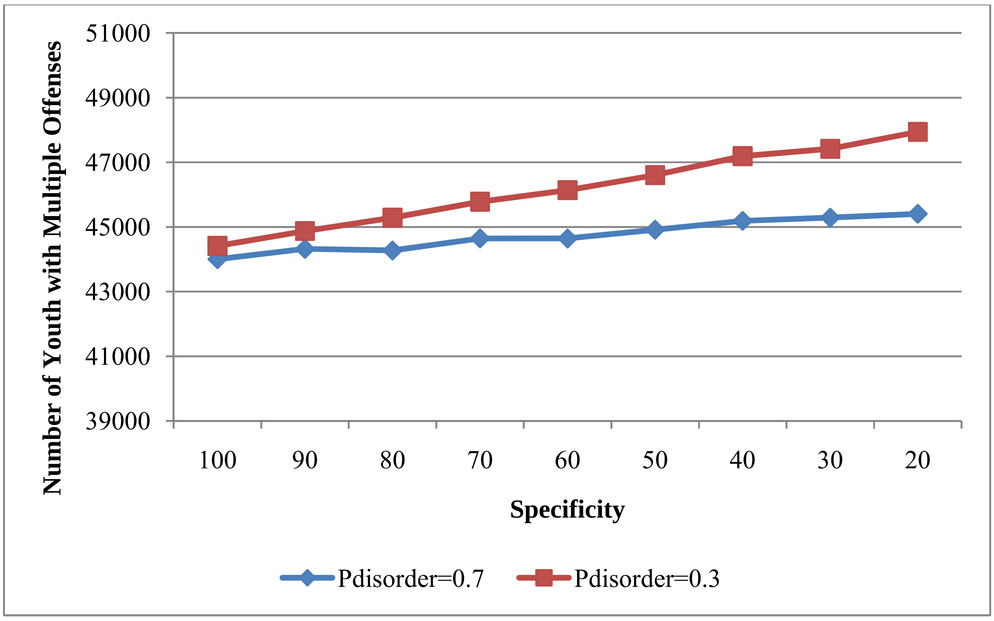
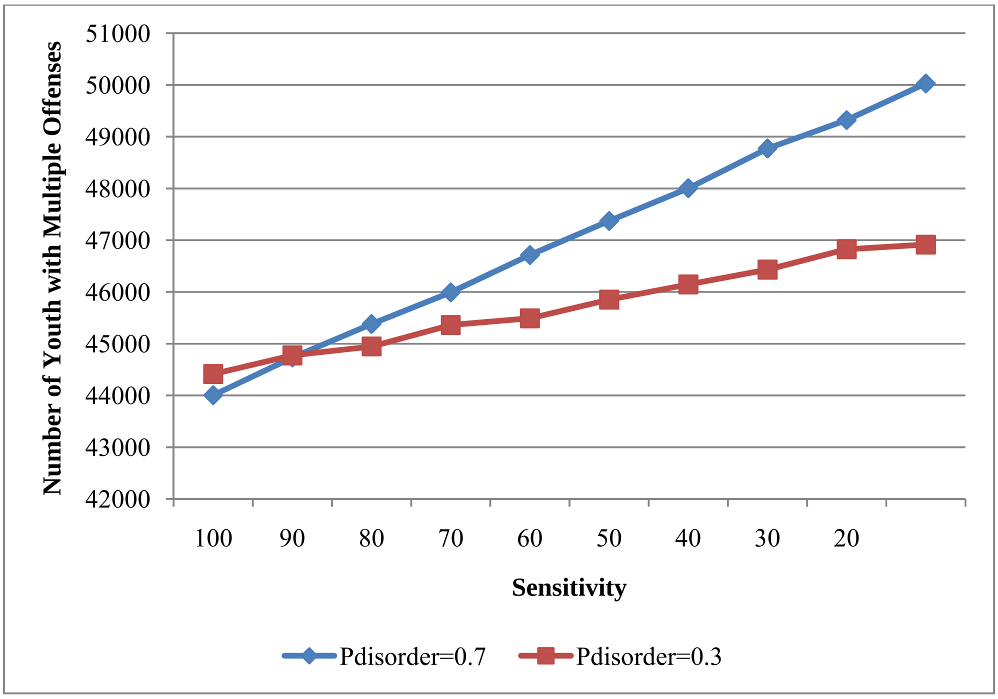
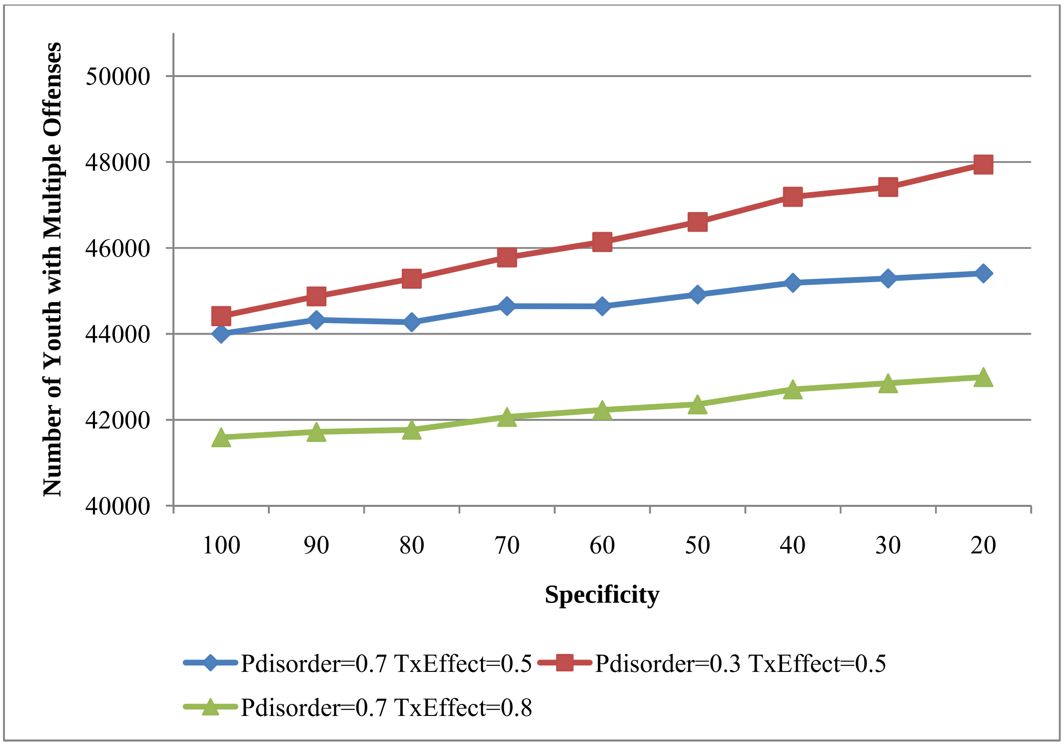


Figure 32. Number of Youth with Multiple Offenses by Sensitivity (Specificity=100%)



analysis, we run additional simulation runs with treatment effect of 0.8. The results are plotted in Figure 33. As we have hypothesized, a treatment that increases the length of stay in the community by 80% creates much less multi-offenders than one that increases length of stay by 50% at the same high prevalence. As to where the line with 30% prevalence and a treatment effect of 0.8 lies, it depends on the intrinsic relationship between the two, and it is difficult to tell without running more simulations.

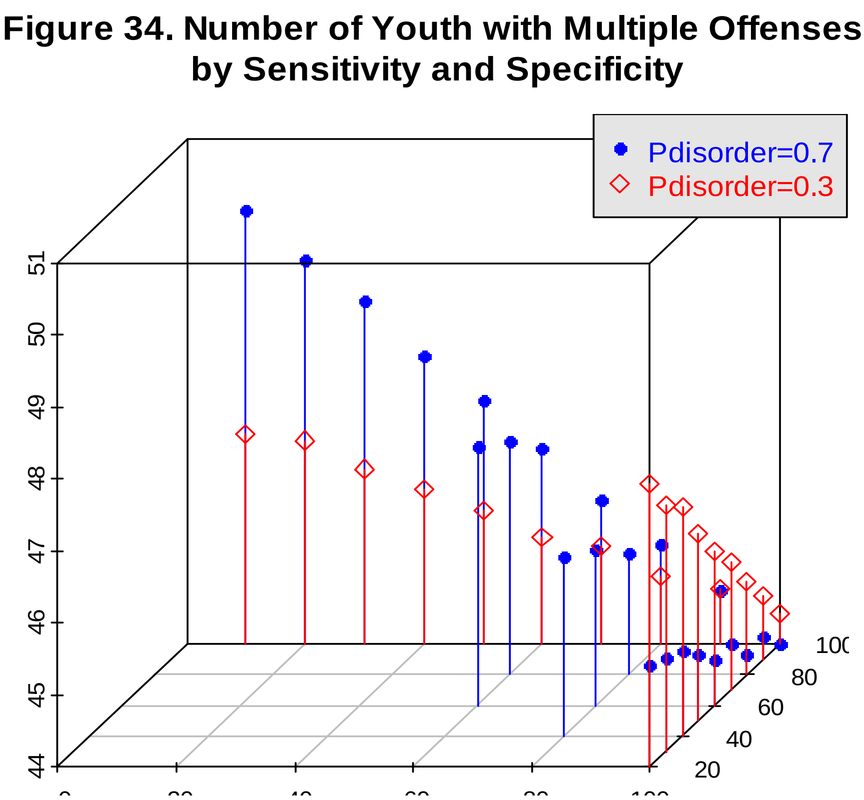
Figure 33. Sensitivity Analysis: Number of Youth with Multiple Offenses by Specificity



In the case of perfect specificity, it is also difficult to tell which effect is better because false negatives miss the treatment while being exposed to “bad effect” that shortens his length of stay, and the relationship between bad effect and the prevalence is nonlinear and not straightforward. We can also see from Figure 32 that the two lines actually cross at the 90% specificity level.

When both sensitivity and specificity are not perfect, their combination may have different effects on the number of multi-offenders exiting the system. Figure 34 plot the effects on 3-dimensional graph. We run several selected scenarios and plot the corresponding points. Ideally one would see a response surface covering all the levels of sensitivity and specificity.

Figure 34. Number of Youth with Multiple Offenses by Sensitivity and Specificity



4.4 Summary

In this chapter, we first decided the warm-up length and number of replications needed for system stabilization and desired precision. Then we examined various individual criminal outcomes and system performance measures across a wide range of policy scenarios regarding resource allocation and screening. A close look at the relationship between treatment capacity, proportion of youth sentenced to treatment, the effect of treatment, screening sensitivity and specificity, mental health service utilization, and crime in a community reveals interesting findings, some of which may be counterintuitive. The next chapter will discuss the study findings, the implications for public health, limitations of current study, recommendations for future research, and conclusion.

CHAPTER 5 DISCUSSION

5.1 Summary of Study Findings

5.1.1 Mental health service utilization.

Treatment capacity.

Based on current caseload, if we divert 100% of high-risk youth from detention to treatment, the total number of youth being treated gradually increases between 100 and 180 slots and then levels up. The number of untreated due to capacity constraint, on the other hand, decreases to 0 when the treatment capacity is 180 slots or more. The pattern is similar for total treatment sessions, service utilization, and total number of high-risk youth treated.

A simple calculation reveals that a treatment capacity that can treat 10% of all the juvenile offenders and 37% of all the high-risk juvenile offenders is sufficient to meet the mental health needs of this juvenile offender population.

Proportion of youth diverted from detention to treatment.

If we fix the treatment capacity to be 100 slots, and gradually decrease the percentage of youth diverted from detention to treatment, the total number of youth being treated remain unchanged between 100% and 60% and gradually decrease. Again this pattern is similar for total treatment sessions, service utilization, and total number of high-risk youth treated.

With current treatment capacity of 100 slots, diverting 100% of high-risk detained youth to mental health service can satisfy 37% of their needs. On the other hand, diverting 60% of high-risk detained youth to mental health service can satisfy 61% of the needs. Both options ultimately treat the same number of youth because 100% diversion indicates more people are lined up waiting for treatment and end up not getting it because they wait for so long.

Effectiveness of treatment.

When we compare service utilization at different levels of treatment effectiveness, we see that at the same level of capacity, a highly effective treatment treats more problem youth, have less treatment sessions, lower percentage of untreated, and lower service utilization as compared to a moderately effective treatment. Meanwhile, at the same level of diverting youth to treatment, a highly effective treatment treats more problem youth, have less treatment sessions, lower percentage of untreated, and lower service utilization as compared to a moderately effective treatment.

Links between factors.

There is a dynamic relationship among the three factors we consider above, and we can achieve the same level of mental health service utilization through a combination of the three factors at varying levels. The real choice depends on other preferences of the policy makers (such as minimize cost or maximize the total number treated).

5.1.2 Criminal outcomes.

Generally speaking, the number or the percentage of youth entering adulthood with multiple offenses is lower for a highly effective treatment, or scenarios with higher proportion of youth diverted to treatment, but not much different for treatment with different capacities. The average number of arrests follow similar pattern. As to the percentage of youth exiting the system with last screened status as high-risk, counterintuitively it is always slightly higher for a highly effective treatment with larger capacity. But it is more of an issue of the model set up and the measure is stabilized across all the scenarios.

5.1.3 Cost-effectiveness analysis.

We focus on the total number of multi-offenders exiting the system as the effectiveness measure. When comparing the two optimal scenarios in terms of total number of youth treated, we see they represent essentially the same incremental cost-effective ratio. When comparing all the scenarios, for a highly effective treatment, the most cost-effective scenario among all considered is a treatment capacity of 100 slots with half high-risk youth diverted from detention to treatment. For a moderately effective treatment, the best one is a treatment capacity of 140 slots with all high-risk youth diverted from detention to treatment. If we compare the two best scenarios for each type of treatment, we see overall the moderately effective treatment with more capacity and higher proportion of diverting youth to treatment has better cost-effectiveness.

5.1.4 Effect of screening.

Generally speaking, the number of multi-offenders increases with decreasing sensitivity or specificity. Under perfect sensitivity, the number of multi-offenders is higher for a detained juvenile population with 30% disorder than the one with 70% disorder. The difference between the two also depends on the treatment effect. The more effective the treatment is, the greater the difference is.

Under perfect specificity, it is difficult to see a clear pattern across sensitivity and prevalence because such relationships also depend on the adverse effect of false positives being exposed to incarceration.

Overall, the relationship is non-linear and several combinations of the factors may produce the same number of multi-offenders exiting the system.

5.2 Implications for Public Health and Juvenile Justice Policy

Juvenile crime remains a serious issue in today's society with its huge societal cost. Although the overall trend for juvenile crime is decreasing in recent years, 2.18 million juveniles were arrested in 2007. They accounted for 16% of all violent crime arrests, and 26% of all property crime arrest. There is increasing awareness of the unmet mental health needs of youth in juvenile justice system. Research has demonstrated that a small proportion of chronic offenders may account for a substantial proportion of the crime and early intervention targeted at this small group of youth may bring enormous benefits to the whole society.

Many alternative community-based programs targeted at youth's social and behavior problems have demonstrated their effectiveness and cost-effectiveness. However, the key question is to provide the right amount of mental health services and to provide them to the right people. These issues essentially involve choosing the most cost-effective strategy of treatment and screening under constrained resources for a target population. Existing studies usually just "feel one part of the elephant".

Discrete-event simulation tools, though originated from industrial and systems engineering, have increasingly been applied to examine social problems. Such tools offer several advantages in economic analysis than traditional methods such as decision trees or Markov models. They provide a multi-level perspective of the analysis, are flexible to model the dynamic relationships among key elements of the social systems, and are flexible to incorporate the randomness, variability, and uncertainty inherent in those systems. In addition, it integrates four tasks typically treated separately, namely, making statistical inference about model parameters, creating alternative policy scenarios for assessment, performing sensitivity analysis with regard to key parameters and assumption, and searching for optimal strategies under certain constraints. [65]

Applying those tools to study the U.S. juvenile justice and mental health systems, this study demonstrates the dynamics among key elements of the systems. Those key elements represent the factors policy makers need to consider when design policies regarding juvenile crime prevention and treatment. For example, when implementing a community-based treatment targeted at high-risk youth, policy makers need to decide the capacity of the treatment, the threshold to divert high-risk youth from detention to treatments, whether to implement a highly effective or a moderately effective treatment, among other factors. The study indicates that for different outcomes policy makers want to achieve, the best strategy may not be the same, and it may well depend on other factors.

This study is a good demonstration of how research tools from other discipline can be applied innovatively and appropriately into a new field. Previous studies have used DES either to study cost-effectiveness of treatments of diseases such as HIV,[37] diabetes,[36] or depression;[35] or to examine final court outcomes for a particular juvenile justice system. This study examines different policies regarding the allocation of mental health treatment resources within juvenile justice system on various individual and system level outcomes. It serves as the basis to advance research in evaluating juvenile crime prevention and mental health treatment in general as well as other social intervention programs. Meanwhile, it serves as the starting point to provide informed support for policymakers in making decisions about allocation of scarce public resources, coordinating various childcare systems in treatment justice-involved youth with mental illness, and planning short-term and long-term strategies for the juvenile justice and the mental health systems.

This study also provides an alternative approach to integrate existing evidence on different intervention and prevention programs targeted at juvenile crime. Published studies vary in terms of the research quality, the target population, and the specific problems the programs treat. At the same time, there is growing recognition of the two salient factors within criminology, namely, the research should not be restricted to the United States, and researchers should do a better job accumulating the knowledge. [66] DES tools thus are especially important to help with generalization of the study results and integration of existing evidence across different settings.

5.3 Study Limitations

There are several limitations to this study. First, we did not consider the differential effect of race or gender in the model, even though we put those as attributes for each individual. We do so based on several considerations. One, we do not have time to gather race- and gender-specific parameter estimates for different components of the model and in some case such estimates are not available at all. Two, at this stage, we are primarily interested in how efficiently the resource is allocated for a juvenile justice system as a whole. Later we can further distinguish systems with different composition of racial and gender groups. Three, research has not found any differential effect of MST treatment on race or gender.[67] Therefore, we did not distinguish the path in the juvenile justice system by race and gender in our model. However, we do provide the demographic information for the juvenile population in Washington State, where we obtain the majority of the estimates from. In that population, the majority of offenders are males (78%), and two thirds are non-Hispanic

White (62%). African American juveniles account for only 4% of the population but 13% of all the sentences. Asian American and Pacific Islanders, on the other hand, account for 6% of the population but only 3% of the sentences. So those figures give people an idea of the type of juvenile justice system our model represents.

Consequently, because we based our model on the Washington State juvenile offender population, there is the question of generalizability of researching findings. One must acknowledge that there is not one, but fifty-one juvenile justice systems in the United States. Each system has its own history and set of laws and policies to follow. And there is hardly any universal estimate available. The purpose of building simulations models is not to completely imitate daily operations of any specific juvenile justice system, but to inform policy makers about the interconnections between key elements of the system, which are not straightforward using conventional analytic technique. Therefore, one always faces the trade-off between the level of details and the generalizability. We do find some estimates of current model are consistent with figures in other places such as Philadelphia. This consistence is assuring. In the meantime, our current model can be either condensed or expanded to fit a particular need for policy analysis.

A third limitation comes from the model specification and data source. While we try to translate a conceptual model as close as possible into a computer program, we have to consider the limitations of the software, the computation speed, etc.. Many of the model setup reflects those limitations. For example, we arbitrary set a maximum waiting period of 90 days for a youth to wait for treatment. And we limit the total run length and the number of replications. Similarly to software, there is no perfect data in the world. One can perform a meta-analysis for every model parameter estimate. But the resource needed is way beyond the scope of this study. We anticipate obtaining individual-level data from Washington state in the future. Such data are helpful to refine some of the model estimates as well as to validate the model.

5.4 Recommendation for Future Research

There are so many things one can further examine either with the current model or with an expanded model. Those things include but are not limited to:

1) Allowing the size of the cohort of juvenile offenders to vary as compared to a constant rate in the current model;
2) Examining the experience of different race or gender groups in the system;
3) Examining the role of age underlying the dynamics of juvenile delinquency and the experience of youth in juvenile justice system;
4) Examining implementing a treatment targeted at combination of high- and moderate-risk factors and how to set up priority for using resource when there is a conflict;
5) Searching for optimal strategy based on a specific budget and other factors;
6) Extending the current model to the adult justice system for treatment of mental disorder;
7) Use a combination of agent-based and discrete-event simulation models to examine the contagious effect an offender may have on peers when he returns to community from incarceration.

As we emphasized before, simulation is limited only by computational capacity, the availability of data to specify relevant parameters, and one's imagination of the knowledge of the systems involved.

5.5 Conclusions

This study is the first to apply DES tools to examine mental health issues within juvenile justice systems. Specifically, the study examines the impact of implementing a community-based treatment programs on the crime in a community, and how that impact depends on key system factors such as the service capacity, the effectiveness of the treatment, and the needs for service. The study demonstrate a nonlinear relationship between those factors-beyond certain capacity or needs, the return from providing additional service diminishes to zero, and the rate of diminishing also depends on the effectiveness of the treatment. In addition, screening is intertwined with the downstream costs and effectiveness of the treatment—the most accurate screening may not be the most cost-effective strategy.

The study demonstrates the feasibility of using tools from other disciplines to examine social policies and to provide decision-support for policy makers. It serves as the basis to examine various social issues in broader social context including child welfare, education, mental health, and juvenile justice.

APPENDICES

Appendix A. Entities

Entity Module Name	Entity	Arrivals	Logic
Kid gets arrested first time	a juvenile	Exponential (0.2)	On average, every 0.2 day there is a first-time juvenile offend entering into the juvenile justice system

Appendix B. Entity Attributes

Entity Attribute Name	User Input	Value	Logic
Sex	Y	DISC(0.26,1,1,2)	Female 25% Male 74%
InitialAge	Y	CONT(0,10,0.0063,11,0.0276,12,0.1022,13,0.2448,14,0.4583,15,0.5953,16,0.7599,17,1,18) (in years)	Continuous distribution between 10 and 17 with the proportion corresponding to the juvenile population under study
TimeIn	N	TNOW	System internal clock
CurrentAge	Y	InitialAge	Initial value
		CurrentAge+(TNOW-TimeIn+Stay)/365 (in years)	being updated each time a duration of stay occurs
Narrest	Y	0	Initial value
		Narrest+1	Updated each time a new arrrest occurs
PreArrest	Y	0	Initial value
		PreArrest+1	Updated each time a new arrrest occurs. Three default values: 0, 1, 2. If more than 2 arrests appeared, this attributed is adjusted to 2.
NTx	Y	0	Initial value
		NTx+1	Updated each time a new treatment session occurs
NDetention	Y	0	Initial value
		NDetention+1	Updated each time a new incarceration occurs
NSupervision	Y	0	Initial value
		NSupervision+1	Updated each time a new community supervision occurs
CurrentOffense	Y	DISC(0.55,1,0.86,2,1,3)	Initial value: Misdemeanor:55%; Non-violent feloney: 31%; Violent felony: 14%
DetentionStay	Y	Expo(183) (in days)	The average duration of stay for incarceration stay is 183 days
MSTStay	Y	TRIA(30,120,180) (in days)	Minimun: 30 days; Maximum: 180 days; most likely duration of stay: 120 days
CommunitySupervisionStay	Y	Expo(205) (in days)	The average duration of stay for Community Supervision Stay stay is 205 days

Appendix B (Cont'd)

Entity Attribute Name	User Input	Value	Logic
Risk	Y	Screen(1+PreArrest)[a]	Screened risk status is a function of the number of previous arrests
		Screen0(CurrentAge-9,CurrentOffense) Screen1(CurrentAge-9,CurrentOffense) Screen2(CurrentAge-9,CurrentOffense)	For each category of arrest history (0,1,2), screened risk status is further a function of current age and current offense
Sentence	Y	ESentence(Risk)[b]	The disposition a juvenile receives during a formal hearing is a function of the screened risk status
Stay	Y	EStay(Risk,Sentence)[c]	Community stay after serving the sentence; representing a form of recidivism; modeled as a function of the screened risk status and the dispostion the juvenile received
PreviousOffense	Y	CurrentOffense	Store the offense type information of the last offense
CurrentOffense	Y	New(PreviousOffense)[d]	Updated based on the type of offense committed before
QArrivalTime	N	TNOW	Record the arrival time when an entity goes to treatment facility and waits in a queue

[a] See Appendix B.1-3

[b] See Appendix B.4

[c] See Appendix B.5

[d] See Appendix B.6

Appendix B.1 Risk=Screen0 (Age-9, Current Offense)

Age-9	Current Offense		
	Misdemeanor	Non-violent Felony	Felony
1	1	1	2
2	1	1	2
3	1	1	2
4	1	1	3
5	1	2	3
6	1	2	3
7	1	2	3
8	1	2	3

Appendix B.2 Risk=Screen1 (Age-9, Current Offense)

Age-9	Current Offense		
	Misdemeanor	Non-violent Felony	Felony
1	1	2	3
2	1	2	3
3	1	2	3
4	2	3	3
5	2	3	3
6	2	3	3
7	2	3	3
8	2	3	3

Appendix B.3 Risk=Screen2 (Age-9, Current Offense)

Age-9	Current Offense		
	Misdemeanor	Non-violent Felony	Felony
1	2	3	3
2	2	3	3
3	3	3	3
4	3	3	3
5	3	3	3
6	3	3	3
7	3	3	3
8	3	3	3

Appendix B.4 ESentence(Risk)

Risk	Sentence[a]	Description
Low	DISC(0.86,2,1,3,41)	Community supervision 86%; incarceration 14%
Moderate	DISC(0.56,2,1,3,42)	Community supervision 56%; incarceration 44%
High	DISC(0.34,2,1,3,43)	Community supervision 34%; incarceration 56%

[a] 2: Community Supervision 3: Detention

Appendix B.5 Community Stay after Sentence=EStay(Risk,Sentence)

Risk Status	Sentence			
	Diversion	Community Supervision	Detention	Mental Health Treatment
Low	Expo(1548,31)	Expo(1263,34)	Expo(821,37)	Expo(3.02*(-18*30.25/ln(1-(1-Effect)*0.867)))
Moderate	Expo(823,32)	Expo(786,35)	Expo(435,38)	Expo(1.88*(-18*30.25/ln(1-(1-Effect)*0.867)))
High	Expo(513,33)	Expo(418,36)	Expo(270,39)	Expo(-18*30.25/ln(1-(1-Effect)*0.867))

Appendix B.6 New Offense=New(PreviousOffense)

Previous Offense	New Offense[a]	Description
Misdemeanor	DISC(0.86,1,0.93,2,1,3,51)	Misdemeanor: 86%; Non-violent Felony 7%; Violent Felony: 7%
Non-violent Felony	DISC(0.375,1,0.625,2,1,3,52)	Misdemeanor: 37.5%; Non-violent Felony 25%; Violent Felony: 37.5%
Violent Felony	DISC(0.43,1,0.86,2,1,3,53)	Misdemeanor: 43%; Non-violent Felony 43%; Violent Felony: 14%

[a] 1: Misdemeanor; 2: Non-violent Felony; 3: Violent Felony

Appendix C. Resources and Queues

Resource Module Name	Resource	Action	Distribution	Unit
Wait for Court	n/a	Delay	Expo(163)	Days
Community-Supervision	n/a	Delay	Expo(205)	Days
Detention	n/a	Delay	Expo(183)	Days
Treatment	bed	Seize Delay Release	TRIA(30,120,180)	Days

Appendix D. Variables

Variable Name	Initial Value	Logic
Effect	0.4	40% reduction in recidivism
pMSTH	0	Percentage of high-risk youth who were originally sentenced to incarceration and later were diverted to receive treatment
pMSTM	n/a	Percentage of moderate-risk youth who were originally sentenced to incarceration and later were diverted to receive treatment

Appendix E. Decisions

Decision Module Name	Type	Percent True	Condition	Logic
Arrest History	2-way by condition		Attribute "PreArrest">=3	If the number of previous arrest is 3 or greater, we adjust the arrest history category by assigning PreArrest=2
Diversion	2-way by chance	PDiversion(Risk)		Low Risk: 92%; Moderate Risk: 20%; High Risk: 0%
To detention	2-way by condition		Attribute "Sentence"==3	
Detention_High Risk	2-way by condition		Attribute "Risk"==3	
AssigntoTxH	2-way by chance	pMSTH		pMSTH% of the high-risk youth who were sentenced to incarceration will be diverted to receive treatment
AssigntoTxM	2-way by chance	pMSTM		pMSTM% of the moderate-risk youth who were sentenced to incarceration will be diverted to receive treatment
Final Disposition	n-way by condition		Attribute "Sentence"==2 or 3, and default is 4	
tx available	2-way by condition		TNOW-QArrivalTime<90	If the waiting time in treatment queue is less than 90 days and the entity gets out of the queue, it indicates that the treatment slot is available
AgeCalculation	2-way by condition		Attribute "CurrentAge">=18	Then the entity exits the current system
ManyOffender	2-way by condition		Attribute "Narrest">=2	
MSTUser	2-way by condition		Attribute "NTx">=1	
High Risk MST User	n-way by condition		Attribute "Risk"==2 or 3, and default is 1	

Appendix F. User-defined Output

Name	Type	Description/Expression
Unmet needs counter	Counter	Number of people who waited in treatment queue for more than 90 days and have to go to incarceration
Count Many Total	Counter	Total number of people who exit the system with 2 or more offenses
Count One Total	Counter	Total number of people who exit the system with only one offenses
MST User Total	Counter	Total number of people who received treatment
Non MST User Total	Counter	Total number of people who did not receive treatment
MSTHUser	Counter	Number of high-risk youth who received treatment
MSTMUser	Counter	Number of moderate-risk youth who received treatment
MSTLUser	Counter	Number of low-risk youth who received treatment
OneCountL	Counter	Number of low-risk youth who only had one offense
ManyCountL	Counter	Number of low-risk youth who had multiple offense
OneCountM	Counter	Number of moderate-risk youth who only had one offense
ManyCountM	Counter	Number of moderate-risk youth who had multiple offense
OneCountH	Counter	Number of high-risk youth who only had one offense
ManyCountH	Counter	Number of high-risk youth who had multiple offense
DetentionAndMST	Counter	Number of youth who received both treatment and incarceration
WaitQ	Time Interval	Number of days waiting in treatment queue
TotalMany	Output	NC(Count Many Total)
PercentHMany	Output	NC(ManyCountH)/NC(Count Many Total)
PercentHTx	Output	NC(MSTHUser)/NC(MST User Total)
PercentDetentionAndMST	Output	NC(DetentionAndMST)/NC(MST User Total)
AverageWaitQ	Tally	WaitQ
WIP	Output	EntitiesWIP(kid)
PercentMany	Output	NC(Count Many Total)/EntitiesOut(kid)
PercentHighRisk	Output	(NC(ManyCountH) + NC(OneCountH)) / EntitiesOut(kid)
UnMetNeeds	Output	NC(Unmet Needs Counter)
ManyH	Output	NC(ManyCountH)
OneH	Output	NC(OneCountH)
OneTotal	Output	NC(Count One Total)

Appendix G. Mental Health Service Utilization Simulation Results

	Control			Response			
Scenario Name	Tx Capacity	% Receive Tx	Tx Effect	Treated	Half Width	Treated HighRisk	Half Width
Base	--	--	--	--	--	--	--
200 beds 100%	200	100	0.8	11647	65	11337	65
180 beds 100%	180	100	0.8	11698	76	11386	77
160 beds 100%	160	100	0.8	11618	88	11314	87
140 beds 100%	140	100	0.8	11443	64	11157	64
120 beds 100%	120	100	0.8	9951	44	9713	46
100 beds 100%	100	100	0.8	8453	38	8253	34
100 beds 90%	100	90	0.8	8453	36	8263	41
100 beds 80%	100	80	0.8	8446	47	8258	49
100 beds 70%	100	70	0.8	8386	41	8202	44
100 beds 60%	100	60	0.8	8390	85	8208	85
100 beds 50%	100	50	0.8	7380	69	7224	62
100 beds 40%	100	40	0.8	6261	75	6135	74
100 beds 30%	100	30	0.8	4929	41	4837	43
100 beds 20%	100	20	0.8	3496	41	3432	39
100 beds 10%	100	10	0.8	1859	24	1829	24
300 beds 100%	300	100	0.4	11784	50	11041	65
200 beds 100%	200	100	0.4	11789	50	11051	50
180 beds 100%	180	100	0.4	11804	91	11069	97
160 beds 100%	160	100	0.4	11137	31	10489	35
140 beds 100%	140	100	0.4	10097	24	9534	34
120 beds 100%	120	100	0.4	8917	40	8422	42
100 beds 100%	100	100	0.4	7645	27	7245	20
100 beds 90%	100	90	0.4	7675	31	7281	34
100 beds 80%	100	80	0.4	7688	30	7301	38
100 beds 70%	100	70	0.4	7709	28	7324	27
100 beds 60%	100	60	0.4	7702	32	7333	26
100 beds 50%	100	50	0.4	7438	46	7080	54
100 beds 40%	100	40	0.4	6293	27	6000	29
100 beds 30%	100	30	0.4	5000	37	4774	40
100 beds 20%	100	20	0.4	3536	26	3388	29
100 beds 10%	100	10	0.4	1877	41	1803	40

Appendix G (Cont'd)

Scenario Name	Control			Response			
	Tx Capacity	% Receive Tx	Tx Effect	TotalTx Sessions	Half Width	Untreated	Half Width
Base	--	--	--	--	--	--	--
200 beds 100%	200	100	0.8	13101	93	0	0
180 beds 100%	180	100	0.8	13142	94	0	0
160 beds 100%	160	100	0.8	13041	95	0	0
140 beds 100%	140	100	0.8	12665	77	293	69
120 beds 100%	120	100	0.8	10819	52	2084	108
100 beds 100%	100	100	0.8	9064	38	3898	103
100 beds 90%	100	90	0.8	9062	38	3021	79
100 beds 80%	100	80	0.8	9045	55	2089	85
100 beds 70%	100	70	0.8	8977	39	1075	110
100 beds 60%	100	60	0.8	8998	77	83	58
100 beds 50%	100	50	0.8	7896	65	0	0
100 beds 40%	100	40	0.8	6614	72	0	0
100 beds 30%	100	30	0.8	5143	46	0	0
100 beds 20%	100	20	0.8	3600	48	0	0
100 beds 10%	100	10	0.8	1887	24	0	0
300 beds 100%	300	100	0.4	16480	80	0	0
200 beds 100%	200	100	0.4	16448	73	0	0
180 beds 100%	180	100	0.4	16261	104	7	8
160 beds 100%	160	100	0.4	14526	31	1084	89
140 beds 100%	140	100	0.4	12749	34	2825	93
120 beds 100%	120	100	0.4	10907	31	4590	102
100 beds 100%	100	100	0.4	9071	22	6362	105
100 beds 90%	100	90	0.4	9102	31	5129	89
100 beds 80%	100	80	0.4	9085	15	3881	124
100 beds 70%	100	70	0.4	9112	24	2555	82
100 beds 60%	100	60	0.4	9103	19	1161	117
100 beds 50%	100	50	0.4	8923	72	6	7
100 beds 40%	100	40	0.4	7338	21	0	0
100 beds 30%	100	30	0.4	5623	39	0	0
100 beds 20%	100	20	0.4	3839	28	0	0
100 beds 10%	100	10	0.4	1956	42	0	0

Appendix G (Cont'd)

Scenario Name	Control			Response			
	Tx Capacity	% Receive Tx	Tx Effect	Proportion Untreated	Half Width	Tx Utilization	Half Width
Base	--	--	--	--	--	--	--
200 beds 100%	200	100	0.8	0.000	0.000	0.729	0.006
180 beds 100%	180	100	0.8	0.000	0.000	0.811	0.005
160 beds 100%	160	100	0.8	0.000	0.000	0.908	0.007
140 beds 100%	140	100	0.8	0.025	0.006	1.000	0.000
120 beds 100%	120	100	0.8	0.173	0.007	1.000	0.000
100 beds 100%	100	100	0.8	0.316	0.006	1.000	0.000
100 beds 90%	100	90	0.8	0.263	0.005	1.000	0.000
100 beds 80%	100	80	0.8	0.198	0.007	1.000	0.000
100 beds 70%	100	70	0.8	0.113	0.011	1.000	0.000
100 beds 60%	100	60	0.8	0.010	0.007	0.996	0.003
100 beds 50%	100	50	0.8	0.000	0.000	0.876	0.008
100 beds 40%	100	40	0.8	0.000	0.000	0.733	0.008
100 beds 30%	100	30	0.8	0.000	0.000	0.572	0.004
100 beds 20%	100	20	0.8	0.000	0.000	0.400	0.004
100 beds 10%	100	10	0.8	0.000	0.000	0.209	0.004
300 beds 100%	300	100	0.4	0.000	0.000	0.605	0.003
200 beds 100%	200	100	0.4	0.000	0.000	0.907	0.004
180 beds 100%	180	100	0.4	0.001	0.001	0.993	0.003
160 beds 100%	160	100	0.4	0.089	0.007	1.000	0.000
140 beds 100%	140	100	0.4	0.219	0.006	1.000	0.000
120 beds 100%	120	100	0.4	0.340	0.005	1.000	0.000
100 beds 100%	100	100	0.4	0.454	0.004	1.000	0.000
100 beds 90%	100	90	0.4	0.401	0.005	1.000	0.000
100 beds 80%	100	80	0.4	0.335	0.007	1.000	0.000
100 beds 70%	100	70	0.4	0.249	0.006	1.000	0.000
100 beds 60%	100	60	0.4	0.131	0.011	1.000	0.000
100 beds 50%	100	50	0.4	0.001	0.001	0.985	0.005
100 beds 40%	100	40	0.4	0.000	0.000	0.808	0.006
100 beds 30%	100	30	0.4	0.000	0.000	0.619	0.004
100 beds 20%	100	20	0.4	0.000	0.000	0.422	0.004
100 beds 10%	100	10	0.4	0.000	0.000	0.212	0.005

Appendix H. Crime Outcomes

	Control			Response		
Scenario Name	Tx Capacity	% Receive Tx	Tx Effect	Total Out	Toal Many	Half-width
Base	100	0	0.4	49974	15515	105
200 beds 100%	200	100	0.8	49847	12847	65
180 beds 100%	180	100	0.8	49884	12900	92
160 beds 100%	160	100	0.8	49831	12859	94
140 beds 100%	140	100	0.8	49925	12789	56
120 beds 100%	120	100	0.8	49890	12754	84
100 beds 100%	100	100	0.8	49912	12811	92
100 beds 90%	100	90	0.8	49920	13054	64
100 beds 80%	100	80	0.8	49901	13317	71
100 beds 70%	100	70	0.8	49897	13587	106
100 beds 60%	100	60	0.8	49923	13903	135
100 beds 50%	100	50	0.8	49916	14199	98
100 beds 40%	100	40	0.8	49962	14431	106
100 beds 30%	100	30	0.8	49919	14688	92
100 beds 20%	100	20	0.8	49935	14986	96
100 beds 10%	100	10	0.8	49969	15276	113
200 beds 100%	200	100	0.4	49979	14615	110
180 beds 100%	180	100	0.4	49970	14579	84
160 beds 100%	160	100	0.4	49980	14358	121
140 beds 100%	140	100	0.4	49978	14373	93
120 beds 100%	120	100	0.4	49982	14335	117
100 beds 100%	100	100	0.4	49982	14298	114
100 beds 90%	100	90	0.4	49980	14432	80
100 beds 80%	100	80	0.4	49973	14582	128
100 beds 70%	100	70	0.4	49960	14706	77
100 beds 60%	100	60	0.4	49967	14827	91
100 beds 50%	100	50	0.4	49946	15007	92
100 beds 40%	100	40	0.4	49967	15119	98
100 beds 30%	100	30	0.4	49957	15231	82
100 beds 20%	100	20	0.4	49984	15358	91
100 beds 10%	100	10	0.4	50014	15455	107

Appendix H (Cont'd)

	Control			Response		
Scenario Name	Tx Capacity	% Receive Tx	Tx Effect	TotalOne	Half-width	TotalNone
Base	100	0	0.4	16975	95	17484
200 beds 100%	200	100	0.8	19559	74	17441
180 beds 100%	180	100	0.8	19556	68	17428
160 beds 100%	160	100	0.8	19468	69	17504
140 beds 100%	140	100	0.8	19640	83	17496
120 beds 100%	120	100	0.8	19671	84	17465
100 beds 100%	100	100	0.8	19614	101	17488
100 beds 90%	100	90	0.8	19389	77	17478
100 beds 80%	100	80	0.8	19110	115	17474
100 beds 70%	100	70	0.8	18854	115	17456
100 beds 60%	100	60	0.8	18540	80	17480
100 beds 50%	100	50	0.8	18226	69	17491
100 beds 40%	100	40	0.8	18011	84	17520
100 beds 30%	100	30	0.8	17759	88	17472
100 beds 20%	100	20	0.8	17468	99	17481
100 beds 10%	100	10	0.8	17207	123	17486
200 beds 100%	200	100	0.4	17909	95	17455
180 beds 100%	180	100	0.4	17914	109	17477
160 beds 100%	160	100	0.4	18142	104	17481
140 beds 100%	140	100	0.4	18133	86	17472
120 beds 100%	120	100	0.4	18188	65	17459
100 beds 100%	100	100	0.4	18196	89	17487
100 beds 90%	100	90	0.4	18105	85	17443
100 beds 80%	100	80	0.4	17933	71	17458
100 beds 70%	100	70	0.4	17816	93	17438
100 beds 60%	100	60	0.4	17643	103	17496
100 beds 50%	100	50	0.4	17507	83	17432
100 beds 40%	100	40	0.4	17389	90	17458
100 beds 30%	100	30	0.4	17239	80	17487
100 beds 20%	100	20	0.4	17148	90	17478
100 beds 10%	100	10	0.4	17088	77	17471

Appendix H (Cont'd)

	Control			Response		
Scenario Name	Tx Capacity	% Receive Tx	Tx Effect	High Risk	Half-width	Med Risk
Base	100	0	0.4	13699	96	10585
200 beds 100%	200	100	0.8	14174	86	9974
180 beds 100%	180	100	0.8	14237	92	9977
160 beds 100%	160	100	0.8	14155	106	10010
140 beds 100%	140	100	0.8	14233	106	9985
120 beds 100%	120	100	0.8	14232	103	9953
100 beds 100%	100	100	0.8	14282	91	9949
100 beds 90%	100	90	0.8	14198	100	10031
100 beds 80%	100	80	0.8	14147	80	10095
100 beds 70%	100	70	0.8	14037	115	10173
100 beds 60%	100	60	0.8	14033	125	10218
100 beds 50%	100	50	0.8	13937	103	10272
100 beds 40%	100	40	0.8	13898	92	10350
100 beds 30%	100	30	0.8	13831	56	10389
100 beds 20%	100	20	0.8	13759	101	10475
100 beds 10%	100	10	0.8	13740	76	10552
200 beds 100%	200	100	0.4	13870	83	10405
180 beds 100%	180	100	0.4	13912	102	10380
160 beds 100%	160	100	0.4	13911	88	10341
140 beds 100%	140	100	0.4	13937	104	10361
120 beds 100%	120	100	0.4	13932	113	10376
100 beds 100%	100	100	0.4	13955	88	10331
100 beds 90%	100	90	0.4	13927	72	10355
100 beds 80%	100	80	0.4	13894	110	10399
100 beds 70%	100	70	0.4	13871	83	10440
100 beds 60%	100	60	0.4	13814	107	10460
100 beds 50%	100	50	0.4	13781	84	10479
100 beds 40%	100	40	0.4	13762	98	10512
100 beds 30%	100	30	0.4	13724	103	10526
100 beds 20%	100	20	0.4	13744	87	10554
100 beds 10%	100	10	0.4	13707	99	10594

Appendix H (Cont'd)

	Control			Response		
Scenario Name	Tx Capacity	% Receive Tx	Tx Effect	Low Risk	Total Arrests	Half-width
Base	100	0	0.4	25690	62187	300
200 beds 100%	200	100	0.8	25698	50984	248
180 beds 100%	180	100	0.8	25670	51088	273
160 beds 100%	160	100	0.8	25665	50876	264
140 beds 100%	140	100	0.8	25707	50748	230
120 beds 100%	120	100	0.8	25704	50602	257
100 beds 100%	100	100	0.8	25681	50646	230
100 beds 90%	100	90	0.8	25692	51517	219
100 beds 80%	100	80	0.8	25659	52331	270
100 beds 70%	100	70	0.8	25688	53329	365
100 beds 60%	100	60	0.8	25672	54482	342
100 beds 50%	100	50	0.8	25708	55693	291
100 beds 40%	100	40	0.8	25715	56811	343
100 beds 30%	100	30	0.8	25700	57955	252
100 beds 20%	100	20	0.8	25700	59288	313
100 beds 10%	100	10	0.8	25677	60731	286
200 beds 100%	200	100	0.4	25704	56832	276
180 beds 100%	180	100	0.4	25678	56486	274
160 beds 100%	160	100	0.4	25728	55389	287
140 beds 100%	140	100	0.4	25680	55313	307
120 beds 100%	120	100	0.4	25674	55269	317
100 beds 100%	100	100	0.4	25696	55123	287
100 beds 90%	100	90	0.4	25698	55754	271
100 beds 80%	100	80	0.4	25679	56395	416
100 beds 70%	100	70	0.4	25649	57126	286
100 beds 60%	100	60	0.4	25693	57765	307
100 beds 50%	100	50	0.4	25687	59050	331
100 beds 40%	100	40	0.4	25693	59827	272
100 beds 30%	100	30	0.4	25707	60355	272
100 beds 20%	100	20	0.4	25686	61056	231
100 beds 10%	100	10	0.4	25713	61673	351

Appendix H (Cont'd)

	Control			Response		
Scenario Name	Tx Capacity	% Receive Tx	Tx Effect	HighRisk%	Half-width	%HighRisk among Chronic Offenders
Base	100	0	0.4	0.274	0.001849	0.711
200 beds 100%	200	100	0.8	0.284	0.00161	0.693
180 beds 100%	180	100	0.8	0.285	0.001474	0.693
160 beds 100%	160	100	0.8	0.284	0.001914	0.691
140 beds 100%	140	100	0.8	0.285	0.001976	0.692
120 beds 100%	120	100	0.8	0.285	0.001772	0.692
100 beds 100%	100	100	0.8	0.286	0.002112	0.691
100 beds 90%	100	90	0.8	0.284	0.001699	0.694
100 beds 80%	100	80	0.8	0.284	0.001664	0.697
100 beds 70%	100	70	0.8	0.281	0.001918	0.697
100 beds 60%	100	60	0.8	0.281	0.002421	0.701
100 beds 50%	100	50	0.8	0.279	0.001776	0.703
100 beds 40%	100	40	0.8	0.278	0.001616	0.705
100 beds 30%	100	30	0.8	0.277	0.001086	0.707
100 beds 20%	100	20	0.8	0.276	0.001647	0.707
100 beds 10%	100	10	0.8	0.275	0.001392	0.708
200 beds 100%	200	100	0.4	0.278	0.00161	0.704
180 beds 100%	180	100	0.4	0.278	0.002136	0.704
160 beds 100%	160	100	0.4	0.278	0.001594	0.701
140 beds 100%	140	100	0.4	0.279	0.001775	0.701
120 beds 100%	120	100	0.4	0.279	0.002152	0.7
100 beds 100%	100	100	0.4	0.279	0.001474	0.701
100 beds 90%	100	90	0.4	0.279	0.001542	0.703
100 beds 80%	100	80	0.4	0.278	0.001783	0.703
100 beds 70%	100	70	0.4	0.278	0.001477	0.705
100 beds 60%	100	60	0.4	0.276	0.001918	0.705
100 beds 50%	100	50	0.4	0.276	0.00153	0.708
100 beds 40%	100	40	0.4	0.275	0.001697	0.71
100 beds 30%	100	30	0.4	0.275	0.002034	0.709
100 beds 20%	100	20	0.4	0.275	0.001634	0.708
100 beds 10%	100	10	0.4	0.274	0.001546	0.71

Appendix H (Cont'd)

Scenario Name	Control			Response		
	Tx Capacity	% Receive Tx	Tx Effect	Half-width	%HighRisk among Treated	Half-width
Base	100	0	0.4	0.002781	1E+20	0
200 beds 100%	200	100	0.8	0.004176	0.973	0.001083
180 beds 100%	180	100	0.8	0.001844	0.973	0.0008423
160 beds 100%	160	100	0.8	0.002411	0.974	0.001375
140 beds 100%	140	100	0.8	0.002902	0.975	0.0007783
120 beds 100%	120	100	0.8	0.002845	0.976	0.001294
100 beds 100%	100	100	0.8	0.003714	0.976	0.001436
100 beds 90%	100	90	0.8	0.002203	0.978	0.001257
100 beds 80%	100	80	0.8	0.003276	0.978	0.001003
100 beds 70%	100	70	0.8	0.002636	0.978	0.001498
100 beds 60%	100	60	0.8	0.002097	0.978	0.0007115
100 beds 50%	100	50	0.8	0.002042	0.979	0.001388
100 beds 40%	100	40	0.8	0.002457	0.98	0.001235
100 beds 30%	100	30	0.8	0.002615	0.981	0.001611
100 beds 20%	100	20	0.8	0.002833	0.982	0.001401
100 beds 10%	100	10	0.8	0.002083	0.984	0.001067
200 beds 100%	200	100	0.4	0.002351	0.937	0.001418
180 beds 100%	180	100	0.4	0.003951	0.938	0.002181
160 beds 100%	160	100	0.4	0.003151	0.942	0.001987
140 beds 100%	140	100	0.4	0.003299	0.944	0.002191
120 beds 100%	120	100	0.4	0.003593	0.944	0.001668
100 beds 100%	100	100	0.4	0.001536	0.948	0.001489
100 beds 90%	100	90	0.4	0.002289	0.949	0.001892
100 beds 80%	100	80	0.4	0.003351	0.95	0.002772
100 beds 70%	100	70	0.4	0.002672	0.95	0.001714
100 beds 60%	100	60	0.4	0.003056	0.952	0.002174
100 beds 50%	100	50	0.4	0.00295	0.952	0.001754
100 beds 40%	100	40	0.4	0.002808	0.953	0.002067
100 beds 30%	100	30	0.4	0.003621	0.955	0.002455
100 beds 20%	100	20	0.4	0.003007	0.958	0.003295
100 beds 10%	100	10	0.4	0.001917	0.96	0.004032

Appendix H (Cont'd)

Scenario Name	Control			Response			
	Tx Capacity	% Receive Tx	Tx Effect	%Chronic Offender	Half-width	Ave Arrest Chronic Offender	Half-width
Base	100	0	0.4	0.3105	0.001942	2.914	0.005355
200 beds 100%	200	100	0.8	0.2577	0.0007998	2.446	0.006456
180 beds 100%	180	100	0.8	0.2586	0.00134	2.444	0.004674
160 beds 100%	160	100	0.8	0.258	0.001566	2.442	0.004214
140 beds 100%	140	100	0.8	0.2562	0.001058	2.432	0.003927
120 beds 100%	120	100	0.8	0.2556	0.001121	2.425	0.004149
100 beds 100%	100	100	0.8	0.2567	0.002009	2.422	0.003156
100 beds 90%	100	90	0.8	0.2615	0.001081	2.461	0.003403
100 beds 80%	100	80	0.8	0.2669	0.001318	2.495	0.004129
100 beds 70%	100	70	0.8	0.2723	0.00193	2.537	0.005437
100 beds 60%	100	60	0.8	0.2785	0.002404	2.585	0.0053
100 beds 50%	100	50	0.8	0.2845	0.001589	2.639	0.003848
100 beds 40%	100	40	0.8	0.2888	0.002159	2.689	0.005081
100 beds 30%	100	30	0.8	0.2942	0.00199	2.737	0.005299
100 beds 20%	100	20	0.8	0.3001	0.00171	2.791	0.00462
100 beds 10%	100	10	0.8	0.3057	0.002093	2.849	0.006495
200 beds 100%	200	100	0.4	0.2924	0.001941	2.663	0.003695
180 beds 100%	180	100	0.4	0.2918	0.001656	2.646	0.005827
160 beds 100%	160	100	0.4	0.2873	0.002128	2.594	0.003751
140 beds 100%	140	100	0.4	0.2876	0.00181	2.587	0.004016
120 beds 100%	120	100	0.4	0.2868	0.001927	2.587	0.00486
100 beds 100%	100	100	0.4	0.2861	0.002022	2.583	0.004374
100 beds 90%	100	90	0.4	0.2888	0.001377	2.609	0.005692
100 beds 80%	100	80	0.4	0.2918	0.002191	2.638	0.008176
100 beds 70%	100	70	0.4	0.2944	0.001126	2.673	0.006249
100 beds 60%	100	60	0.4	0.2967	0.001924	2.706	0.005981
100 beds 50%	100	50	0.4	0.3005	0.001594	2.768	0.005364
100 beds 40%	100	40	0.4	0.3026	0.001832	2.807	0.006371
100 beds 30%	100	30	0.4	0.3049	0.001623	2.831	0.005903
100 beds 20%	100	20	0.4	0.3073	0.001754	2.859	0.003098
100 beds 10%	100	10	0.4	0.309	0.001757	2.885	0.006275

Appendix I. Cost-Effectiveness Analysis

	Response					
Scenario Name	ToalMany	Half-width	TotalMany Lower	TotalMany Upper	Ave Cost for Chronic Offender	Half-width
Baseline	15515.4	105	15411	15620	6722.306	21.28
200 beds 100% (0.8)	12847.1	65	12782	12912	6761.738	25.94
180 beds 100% (0.8)	12899.7	92	12808	12991	6748.422	15.29
160 beds 100% (0.8)	12858.8	94	12765	12952	6732.513	12.5
140 beds 100% (0.8)	12789.4	56	12733	12846	6644.694	15.46
120 beds 100% (0.8)	12754.2	84	12670	12839	6454.977	14.1
100 beds 100% (0.8)	12810.8	92	12719	12903	6285.565	20.61
100 beds 90% (0.8)	13053.7	64	12990	13118	6391.1	14.81
100 beds 80% (0.8)	13316.5	71	13245	13388	6472.792	9.776
100 beds 70% (0.8)	13587.3	106	13482	13693	6567.338	13.17
100 beds 60% (0.8)	13903	135	13768	14038	6702.809	19.71
100 beds 50% (0.8)	14199	98	14101	14297	6759.9	13.94
100 beds 40% (0.8)	14430.8	106	14325	14537	6749.388	9.106
100 beds 30% (0.8)	14688.2	92	14597	14780	6739.888	11.99
100 beds 20% (0.8)	14985.8	96	14890	15082	6734.86	15.31
100 beds 10% (0.8)	15276	113	15163	15389	6728.206	10.25
200 beds 100% (0.4)	14614.7	110	14505	14724	7755.819	14.29
180 beds 100% (0.4)	14579.4	84	14495	14664	7678.638	15.21
160 beds 100% (0.4)	14357.9	121	14237	14479	7334.881	18.01
140 beds 100% (0.4)	14372.7	93	14279	14466	7152.586	20.59
120 beds 100% (0.4)	14334.7	117	14218	14452	6962.981	19.9
100 beds 100% (0.4)	14298.4	114	14185	14412	6779.271	17.18
100 beds 90% (0.4)	14431.7	80	14351	14512	6851.187	9.869
100 beds 80% (0.4)	14581.7	128	14454	14710	6917.767	17.61
100 beds 70% (0.4)	14706.1	77	14630	14783	6997.119	23.56
100 beds 60% (0.4)	14827.3	91	14736	14919	7084.281	14.69
100 beds 50% (0.4)	15007	92	14915	15099	7239.878	14.37
100 beds 40% (0.4)	15119.2	98	15021	15218	7182.242	13.78
100 beds 30% (0.4)	15231.2	82	15150	15313	7068.891	21.59
100 beds 20% (0.4)	15357.7	91	15267	15448	6959.581	16.22
100 beds 10% (0.4)	15455.1	107	15348	15562	6838.129	21.91

Appendix I (Cont'd)

	Response					
Scenario Name	Total Cost	Total Cost Lower	Total CostUpper	Incremental Effect	Incremental Cost	ICER
Baseline	104299266.5	103267501.4	105335487.7			
200 beds 100% (0.8)	86868724.26	86099933.79	87640869.29	2668.3	-17,430,542	-6532.45
180 beds 100% (0.8)	87052619.27	86237550.67	87870493.9	2615.7	-17,246,647	-6593.51
160 beds 100% (0.8)	86572038.16	85782780.35	87363634.23	2656.6	-17,727,228	-6672.90
140 beds 100% (0.8)	84981649.44	84410633.15	85554406.84	2726	-19,317,617	-7086.43
120 beds 100% (0.8)	82328067.65	81604623.41	83053891.97	2761.2	-21,971,199	-7957.12
100 beds 100% (0.8)	80523116.1	79681707.26	81368323.78	2704.6	-23,776,150	-8791.00
100 beds 90% (0.8)	83427502.07	82825839.16	84031061.84	2461.7	-20,871,764	-8478.60
100 beds 80% (0.8)	86194934.67	85602905.44	86788361.08	2198.9	-18,104,332	-8233.36
100 beds 70% (0.8)	89232391.61	88360015.89	90107554.09	1928.1	-15,066,875	-7814.36
100 beds 60% (0.8)	93189153.53	92010233.79	94373410.73	1612.4	-11,110,113	-6890.42
100 beds 50% (0.8)	95983820.1	95125524.02	96844845.36	1316.4	-8,315,446	-6316.81
100 beds 40% (0.8)	97399068.35	96553191.59	98246875.58	1084.6	-6,900,198	-6361.98
100 beds 30% (0.8)	98996822.92	98204032.27	99791811.58	827.2	-5,302,444	-6410.11
100 beds 20% (0.8)	100927265	100053897.9	101803566.4	529.6	-3,372,002	-6367.07
100 beds 10% (0.8)	102780074.9	101863023.2	103699447.1	239.4	-1,519,192	-6345.83
200 beds 100% (0.4)	113348967.9	112292426.5	114408638.9	900.7	9,049,701	10047.41
180 beds 100% (0.4)	111949934.9	111083074.8	112819355.7	936	7,650,668	8173.79
160 beds 100% (0.4)	105313487.9	104166634	106464714.7	1157.5	1,014,221	876.22
140 beds 100% (0.4)	102801972.8	101840338.4	103767450.9	1142.7	-1,497,294	-1310.31
120 beds 100% (0.4)	99812243.74	98715337.04	100913803.1	1180.7	-4,487,023	-3800.31
100 beds 100% (0.4)	96932728.47	95917556	97951811.1	1217	-7,366,538	-6053.03
100 beds 90% (0.4)	98874275.43	98182627.97	99567507.45	1083.7	-5,424,991	-5005.99
100 beds 80% (0.4)	100872803.1	99731419.2	102018702.1	933.7	-3,426,463	-3669.77
100 beds 70% (0.4)	102900331.7	102020030.1	103784240.4	809.3	-1,398,935	-1728.57
100 beds 60% (0.4)	105040759.7	104177634.4	105906566.8	688.1	741,493	1077.60
100 beds 50% (0.4)	108648849.1	107770764	109529569.2	508.4	4,349,583	8555.43
100 beds 40% (0.4)	108589753.2	107675890.6	109506328.3	396.2	4,290,487	10829.09
100 beds 30% (0.4)	107667692.6	106763368.4	108575542.9	284.2	3,368,426	11852.31
100 beds 20% (0.4)	106883157.1	106004639.6	107764615.4	157.7	2,583,891	16384.85
100 beds 10% (0.4)	105683967.5	104613966	106758670.9	60.3	1,384,701	22963.53

REFERENCES

1. U.S. Public Health Service. Report of the Surgeon General's Conference on Children's Mental Health: A national action agenda. Washington, DC: Department of Health and Human Services; 2000.

2. Teplin LA, Abram KM, McClelland GM, Dulcan MK, Mericle AA. Psychiatric disorders in youth in juvenile detention. In: Am Med Assoc; 2002. p. 1133-1143.

3. Cocozza JJ, Skowyra K. Youth with mental health disorders: Issues and emerging responses. Juvenile Justice 2000;7(1):3-13.

4. Wasserman GA, Ko SJ, McReynolds LS. Assessing the Mental Health Status of Youth in Juvenile Justice Settings: U.S. Department of Justice, Office of Justice Programs, Office of Juvenile Justice and Delinquency Prevention; 2004.

5. Shufelt JL, Cocozza JJ. Youth with mental health disorders in the juvenile justice system: Results from a multi-state prevalence study. Delmar, NY: National Center for Mental Health and Juvenile Justice; 2006.

6. Kelton WD, Sadowski RP, Sturrock DT. Simulation with ARENA. 4 ed: McGraw-Hill Science Engineering; 2003.

7. Puzzanchera C. Juvenile arrests 2007. Juvenile Justice Bulletin 2009.

8. Cohen MA, Piquero AR. New evidence on the monetary value of saving a high risk youth. Journal of Quantitative Criminology 2009;25(1):25-49.

9. Piquero A, Farrington D, Blumstein A. The criminal career paradigm. In: Tonry M, editor. Crime and justice: a review of research. Chicago: University of Chicago Press; 2003.

10. Loeber R, Farrington DP, Waschbush DA. Serious and violent juvenile offenders. In: Loeber R, Farrington DP, editors. Serious and violent juvenile offenders: Risk factors and successful interventions. Thousand Oaks, CA: Sage; 1998. p. 13-29.

11. Farrington DP. Key results from the first forty years of the Cambridge study in delinquent development. In: Thornberry TP, Krohn MD, editors. Taking stock of delinquency: An overview of findings from contemporary longitudinal studies. Boston: Kluwer; 2003. p. 137-183.

12. McCord J, Widom CS, Crowell NA. Juvenile crime, juvenile justice: National Academy Press; 2001.

13. Skowyra K, Cocozza JJ. A blueprint for change: Improving the system response to youth with mental health needs involved with the juvenile justice system. In: National Center for Mental Health and Juvenile Justice; 2006.

14. Elliott DS, Ageton SS, Huizinga D, Knowles BA, Canter RJ. The prevalence and incidence of delinquent behavior: 1976-1980. Boulder, CO: Behavioral Research Institute; 1983.

15. Elliott DS, Huizinga D. The relationship between delinquent behavior and ADM problems. In: Hampton C, editor. Juvenile Offenders With Serious Drug, Alcohol and Mental Health Problems. Washington, DC: U.S. Government Printing Office; 1989.

16. Elliott DS, Huizinga D, Menard S. Multiple problem youth: Delinquency, substance use, and mental health problems. New York: Springer Verlag; 1989.

17. Child delinquents: Development, intervention, and service needs. In: Loeber R, Farrington DP, editors. Thousand Oaks, CA: Sage Publications; 2001.

18. Cottle CC, Lee RJ, Heilbrun K. The prediction of criminal recidivism in juveniles: A meta-analysis. Criminal Justice and Behavior 2001;28(3):367.

19. Loeber R, Dishion T. Early predictors of male delinquency: A review. Psychological Bulletin 1983;94(1):68.

20. Simourd L, Andrews DA. Correlates of delinquency: A look at gender differences. Forum on Corrections Research 1994;6(1):26-31.

21. Lennings CJ, Kenny DT, Nelson P. Substance use and treatment seeking in young offenders on community orders. Journal of Substance Abuse Treatment 2006;31(4):425-432.

22. Johnson TP, Cho YI, Fendrich M, Graf I, Kelly-Wilson L, Pickup L. Treatment need and utilization among youth entering the juvenile corrections system. Journal of substance abuse treatment 2004;26(2):117-128.

23. Domalanta DD, Risser WL, Roberts RE, Hale Risser JM. Prevalence of depression and other psychiatric disorders among incarcerated youths. Journal of the American Academy of Child and Adolescent Psychiatry 2003;42(4):477-484.

24. Redding RE. The Effects Of Adjudicating And Sentencing Juveniles As Adults: Research and Policy Implications. Youth Violence and Juvenile Justice 2003;1(2):128-155.

25. Wooldredge JD. Differentiating the Effects of Juvenile Court Sentences on Eliminating Recidivism. Journal of Research in Crime and Delinquency 1988;25(3):264-300.

26. Belenko S, Logan TK. Delivering more effective treatment to adolescents: Improving the juvenile drug court model. J Subst Abuse Treat 2003;25(3):189-211.

27. Sexton TL, Gilman L, Johnson—Erickson C. Evidence-Based Practices. In: Handbook of Adolescent Behavioral Problems; 2005. p. 101-128.

28. Henggeler SW, Schoenwald SK, Borduin CM, Rowlands MD, Cunningham PB. Multisystemic treatment of antisocial behavior in children and adolescents. New York: Guilford Press; 1998.

29. Henggeler SW, Schoenwald SK, Borduin CM, Rowland MD, Cunningham PB. Multisystemic treatment of antisocial behavior in children and adolescents. 2nd ed: The Guilford Press; 2009.

30. Aos S, Barnoski R. Watching the bottom line: Cost-effective interventions for reducing crime in Washington (RCW 13.40. 500). Olympia, WA: Washington State Institute for Public Policy 1998.

31. Aos S, Phipps P, Barnoski R, Lieb R. The comparative costs and benefits of programs to reduce crime version 4.0: Washington State Institute for Public Policy 2001.

32. Banks J, Carson JS, Nelson BL, Nicol DM. Discrete-event system simulation: Prentice Hall Budapest, Hungary; 2001.

33. Brennan A, Chick S, Davies R. A taxonomy of model structures for economic evaluation of health technologies. Health economics 2006;15(12):1295-1310.

34. Stevenson MD, Simpson EL, Rawdin AC, Papaioannou DE. A review of discrete event simulation in National Coordinating Centre for Health Technology Assessment-funded work and a case study exploring the cost-effectiveness of testing for thrombophilia in patients presenting with an initial idiopathic venous thromboembolism. Journal of Simulation 2010;4(1):14-23.

35. Le Lay A, Despiegel N, François C, Duru G. Can discrete event simulation be of use in modelling major depression? Cost Effectiveness and Resource Allocation 2006;4(1):19.

36. McRae IS, Butler JRG, Sibthorpe BM, Ruscoe W, Snow J, Rubiano D, et al. A cost effectiveness study of integrated care in health services delivery: a diabetes program in Australia. BMC Health Services Research 2008;8(1):205.

37. Simpson KN, Strassburger A, Jones WJ, Dietz B, Rajagopalan R. Comparison of Markov model and discrete-event simulation techniques for HIV. Pharmacoeconomics 2009;27(2):159-165.

38. Gunal MM, Pidd M. Discrete event simulation for performance modelling in health care: a review of the literature. Journal of Simulation 2010;4(1):42-51.

39. Blumstein A. Crime Modeling. Operations Research 2002;50(1):16-24.

40. Stewart A. Justice modelling in the United States of America. In: National Criminal Justice Modelling Workshop; 2001; Queensland, Australia; 2001.

41. Maltz MD. Operations research in studying crime and justice: Its history and accomplishments. In: Pollock SM, Rothkopf MH, Barnett A, editors. Operations Research and the Public Sector. Amsterdam and New York: North-Holland; 1994.

42. Barnett A, P.Caulkins J, Maltz MD. Crime and justice. In: Gass SI, Harris CM, editors. Encyclopedia of Operations Research and Management Science. 2nd ed. Boston, MA: Kluwer Academic Publishers; 2000.

43. Maltz MD. From Poisson to present: applying operations research to problems of crime and justice. Journal of Qualitative Criminology 1996;12(1):3-61.

44. Stewart A, Spencer N, O'Connor I, Palk G, Livingston M, Allard T. Juvenile Justice Simulation Model: A Report on the Australian Research Council Strategic Partnerships with Industry Research and Training Grant No C001069831.; 2004.

45. Livingston MJ, Stewart AL, Palk GJ, Toni M. A micro-simulation model of the juvenile justice system in Queensland: Australian Institute of Criminology; 2006.

46. Law AM, Kelton WD. Simulation modeling and analysis. 4 ed: McGraw-Hill Higher Education; 2007.

47. Rockwell Automation. Arena User's Guide. In. 10.0 ed. Sewickley, Pennsylvania; 2005.

48. Snyder HN, Sickmund M. Juvenile Offenders and Victims: 2006 National Report. Office of Juvenile Justice and Delinquency Prevention 2006:253.

49. Drake E, Barnoski R. The Effects of Parole on Recidivism: Juvenile Offenders Released from Washington State Institutions: Final Report. Olympia, WA: Washington State Institute for Public Policy; 2006.

50. Recidivism of juvenile offenders-Fiscal year 2005: Sentencing Guidelines Commission, State of Washington; 2005 December 2005.

51. Aos S, Miller MG, Drake E, Washington State Institute for Public P. Evidence-based Public Policy Options to Reduce Future Prison Construction, Criminal Justice Costs, and Crime Rates: Washington State Institute for Public Policy; 2006.

52. First-Time Juvenile Offenders in Washington State: Where Do They Serve Their Sentences?: Washington State Institute for Public Policy; 1996.

53. Barnoski R. Assessing risk for re-offense: validating the Washington State Juvenile Court assessment appendices. In: Olympia, WA: Washington State Institute for Public Policy; 2004.

54. Washington State Department of Social and Health Services. 2008 Juvenile Justice Report Data Analysis Section 11: Arrest. In.

55. Research on effectiveness. In: Multisystemic Therapy - MST.

56. Piquero AR, Farrington DP, Blumstein A. Key Issues in Criminal Career Research: Cambridge University Press; 2007.

57. The State Juvenile Justice Profiles. In.

58. Wu L, Rhyne C. Youth Who Received Informal Handling/Supervision in 2006. In: Multnomah County of Oregon Department of Community Justice; 2006.

59. Timmons-Mitchell J, Bender MB, Kishna MA, Mitchell CC. An independent effectiveness trial of multisystemic therapy with juvenile justice youth. Journal of Clinical Child & Adolescent Psychology 2006;35(2):227-236.

60. Sargent RG. Validation and verification of simulation models. In: Proceedings of the 1999 Winter Simulation Conference; 1999; 1999. p. 39-48.

61. Altiok T, Melamed B. Simulation Modeling and analysis with Arena: Academic Press; 2007.

62. Welch PD. On the problem of the initial transient in steady-state simulation. IBM Watson Research Center 1981.

63. Washington State Juvenile Courts: Workloads and Costs. Olympia, Washington: Washington State Institute for Public Policy; 1997.

64. Wolfgang ME, Figlio RM, Sellin T. Delinquency in a birth cohort: University of Chicago Press; 1987.

65. Parmigiani G. Modeling in medical decision making: a Bayesian approach: John Wiley & Sons, Ltd.; 2002.

66. Bersani BE, Nieuwbeerta P, Laub JH. Predicting Trajectories of Offending over the Life Course: Findings from a Dutch Conviction Cohort. Journal of Research in Crime and Delinquency 2009;46(4):468.

67. Cartwright WS, Kitsantas P, Rose SR. A demographic-economic model for adolescent substance abuse and crime prevention. Journal of Comparative Social Welfare 2009;25(2):157-172.